The Profitability of Technical Analysis: A Review

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Abstract

The purpose of this report is to review the evidence on the profitability of technical analysis. To achieve this purpose, the report comprehensively reviews survey, theoretical and empirical studies regarding technical trading strategies. We begin by overviewing survey studies that have directly investigated market participants' experience and views on technical analysis. The survey literature indicates that technical analysis has been widely used by market participants in futures markets and foreign exchange markets, and that about 30% to 40% of practitioners appear to believe that technical analysis is an important factor in determining price movement at shorter time horizons up to 6 months. Then we provide an overview of theoretical models that include implications about the profitability of technical analysis. Conventional efficient market theories, such as the martingale model and random walk models, rule out the possibility of technical trading profits in speculative markets, while relatively recent models such as noisy rational expectation models or behavioral models suggest that technical trading strategies may be profitable due to noise in the market or investors' irrational behavior. Finally, empirical studies are surveyed. In this report, the empirical literature is categorized into two groups, "early" and "modern" studies, according to the characteristics of testing procedures.

Early studies indicated that technical trading strategies were profitable in foreign exchange markets and futures markets, but not in stock markets before the 1980s. Modern studies indicated that technical trading strategies consistently generated economic profits in a variety of speculative markets at least until the early 1990s. Among a total of 92 modern studies, 58 studies found positive results regarding technical trading strategies, while 24 studies obtained negative results. Ten studies indicated mixed results. Despite the positive evidence on the profitability of technical trading strategies, it appears that most empirical studies are subject to various problems in their testing procedures, e.g., data snooping, ex post selection of trading rules or search technologies, and difficulties in estimation of risk and transaction costs. Future research must address these deficiencies in testing in order to provide conclusive evidence on the profitability of technical trading strategies.

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Introduction

Technical analysis is a forecasting method of price movements using past prices, volume, and open interest.[2] Pring (2002), a leading technical analyst, provides a more specific definition:

> "The technical approach to investment is essentially a reflection of the idea that prices move in trends that are determined by the changing attitudes of investors toward a variety of economic, monetary, political, and psychological forces. The art of technical analysis, for it is an art, is to identify a trend reversal at a relatively early stage and ride on that trend until the weight of the evidence shows or proves that the trend has reversed." (p. 2)

Technical analysis includes a variety of forecasting techniques such as chart analysis, pattern recognition analysis, seasonality and cycle analysis, and computerized technical trading systems. However, academic research on technical analysis is generally limited to techniques that can be expressed in mathematical forms, namely technical trading systems, although some recent studies attempt to test visual chart patterns using pattern recognition algorithms. A technical trading system consists of a set of trading rules that result from parameterizations, and each trading rule generates trading signals (long, short, or out of market) according to their parameter values. Several popular technical trading systems are moving averages, channels, and momentum oscillators.

Since Charles H. Dow first introduced the Dow theory in the late 1800s, technical analysis has been extensively used among market participants such as brokers, dealers, fund managers, speculators, and individual investors in the financial industry.[3] Numerous surveys indicate that practitioners attribute a significant role to technical analysis. For example, futures fund managers rely heavily on computer-guided technical trading systems (Irwin and Brorsen 1985; Brorsen and Irwin 1987; Billingsley and Chance 1996), and about 30% to 40% of foreign exchange traders around the world believe that technical analysis is the major factor determining exchange rates in the short-run up to six months (e.g., Menkhoff 1997; Cheung and Wong 2000; Cheung, Chinn, and Marsh 2000; Cheung and Chinn 2001).

In contrast to the views of many practitioners, most academics are skeptical about technical analysis. Rather, they tend to believe that markets are informationally efficient and hence all available information is impounded in current prices (Fama 1970). In efficient markets, therefore, any attempts to make profits by exploiting currently available information are futile. In a famous passage, Samuelson (1965) argues that:

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[2] In futures markets, open interest is defined as "the total number of open transactions" (Leuthold, Junkus, and Cordier 1989).

[3] In fact, the history of technical analysis dates back to at least the 18th century when the Japanese developed a form of technical analysis known as candlestick charting techniques. This technique was not introduced to the West until the 1970s (Nison 1991).

> "…there is no way of making an expected profit by extrapolating past changes in the futures price, by chart or any other esoteric devices of magic or mathematics. The market quotation already contains in itself all that can be known about the future and in that sense has discounted future contingencies as much as is humanly possible." (p. 44)

Nevertheless, in recent decades rigorous theoretical explanations for the widespread use of technical analysis have been developed based on noisy rational expectation models (Treynor and Ferguson 1985; Brown and Jennings 1989; Grundy and McNichols 1989; Blume, Easley, and O'Hara 1994), behavioral (or feedback) models (De Long et al. 1990a, 1991; Shleifer and Summers 1990), disequilibrium models (Beja and Goldman 1980), herding models (Froot, Scharfstein, and Stein 1992), agent-based models (Schmidt 2002), and chaos theory (Clyde and Osler 1997). For example, Brown and Jennings (1989) demonstrated that under a noisy rational expectations model in which current prices do not fully reveal private information (signals) because of noise (unobserved current supply of a risky asset) in the current equilibrium price, historical prices (i.e., technical analysis) together with current prices help traders make more precise inferences about past and present signals than do current prices alone (p. 527).

Since Donchian (1960), numerous empirical studies have tested the profitability of technical trading rules in a variety of markets for the purpose of either uncovering profitable trading rules or testing market efficiency, or both. Most studies have concentrated on stock markets, both in the US and outside the US, and foreign exchange markets, while a smaller number of studies have analyzed futures markets. Before the mid-1980s, the majority of the technical trading studies simulated only one or two trading systems. In these studies, although transaction costs were deducted to compute net returns of technical trading strategies, risk was not adequately handled, statistical tests of trading profits and data snooping problems were often disregarded, and out-of-sample verification along with parameter (trading rule) optimization were not considered in the testing procedure. After the mid-1980s, however, technical trading studies greatly improved upon the drawbacks of early studies and typically included some of the following features in their testing procedures: (1) the number of trading systems tested increased relative to early studies; (2) returns were adjusted for transaction costs and risk; (3) parameter (trading rule) optimization and the out-of-sample verification were conducted; and (4) statistical tests were performed with either conventional statistical tests or more sophisticated bootstrap methods, or both.

The purpose of this report is to review the evidence on the profitability of technical analysis. To achieve this purpose, the report comprehensively reviews survey, theoretical and empirical studies regarding technical analysis and discusses the consistency and reliability of technical trading profits across markets and over time. Despite a recent explosion in the literature on technical analysis, no study has surveyed the literature systematically and comprehensively. The report will pay special attention to testing procedures used in empirical studies and identify their salient features and weaknesses. This will improve general understanding of the profitability of technical trading strategies and suggest directions for future research. Empirical studies surveyed include those that tested technical trading systems, trading rules formulated by genetic algorithms or some statistical models (e.g., ARIMA), and chart patterns that can be represented algebraically. The majority of the studies were collected from academic journals published from 1960 to the present and recent working papers. Only a few studies were obtained from books or magazines.

Survey Studies

Survey studies attempt to directly investigate market participants' behavior and experiences, and document their views on how a market works. These features cannot be easily observed in typical data sets. The oldest survey study regarding technical analysis dates back to Stewart (1949), who analyzed the trading behavior of customers of a large Chicago futures commission firm over the 1924-1932 period. The result indicated that in general traders were unsuccessful in their grain futures trading, regardless of their scale and knowledge of the commodity traded. Amateur speculators were more likely to be long than short in futures markets. Long positions generally were taken on days of price declines, while short positions were initiated on days of price rises. Thus, trading against the current movement of prices appeared to be dominant. However, a representative successful speculator showed a tendency to buy on reversals in price movement during upward price swings and sell on upswings that followed declines in prices, suggesting that successful speculators followed market trends.

Smidt (1965a) surveyed trading activities of amateur traders in the US commodity futures markets in 1961.[4] In this survey, about 53% of respondents claimed that they used charts either exclusively or moderately in order to identify trends. The chartists, whose jobs hardly had relation to commodity information, tended to trade more commodities in comparison to the other traders (non-chartists). Only 24% of the chartists had been trading for six or more years, while 42% of non-chartists belonged to the same category. There was a slight tendency for chartists to pyramid more frequently than other traders.[5] It is interesting to note that only 10% of the chartists, compared to 29% of the non-chartists, nearly always took long positions.

The Group of Thirty (1985) surveyed the views of market participants on the functioning of the foreign exchange market in 1985. The respondents were composed of 40 large banks and 15 securities houses in 12 countries. The survey results indicated that 97% of bank respondents and 87% of the securities houses believed that the use of technical analysis had a significant impact on the market. The Group of Thirty reported that "Technical trading systems, involving computer models and charts, have become the vogue, so that the market reacts more sharply to short term trends and less attention is given to basic factors (p. 14)."

Brorsen and Irwin (1987) carried out a survey of large public futures funds' advisory groups in 1986. In their survey, more than half of the advisors responded that they relied heavily on computer-guided technical trading systems. Most fund advisors appeared to use technical trading rules by optimizing parameters of their trading systems over historical data whose amounts varied by advisors, with two years being the smallest amount. Because of liquidity costs, futures funds held 80% of their positions in the nearby contract, and the average number of

[4] In this survey, an amateur trader was defined as "a trader who was not a hedger, who did not earn most of his income from commodity trading, and who did not spend most of his time in commodity trading (p. 7)."

[5] Pyramiding occurs when a trader adds to the size of his/her open position after a price has moved in the direction he/she had predicted.

commodities they traded had been quite constant through time. Since technically traded public and private futures funds were estimated to control an average of 23% of the open interest in ten important futures markets, the funds seemed large enough to move prices if they traded in unison (p. 133).

Frankel and Froot (1990) showed that switching a forecasting method for another over time may explain changes in the demand for dollars in foreign exchange markets. The evidence provided was the survey results of *Euromoney* magazine for foreign exchange forecasting firms. According to the magazine, in 1978, nineteen forecasting firms exclusively used fundamental analysis and only three firms technical analysis. After 1983, however, the distribution had been reversed. In 1983, only one firm reported using fundamental analysis, and eight technical analysis. In 1988, seven firms appeared to rely on fundamental analysis while eighteen firms employed technical analysis.

Taylor and Allen (1992) conducted a survey on the use of technical analysis among chief foreign exchange dealers in the London market in 1988. The results indicated that 64% of respondents reported using moving averages and/or other trend-following systems and 40% reported using other trading systems such as momentum indicators or oscillators. In addition, approximately 90% of respondents reported that they were using some technical analysis when forming their exchange rate expectations at the shortest horizons (intraday to one week), with 60% viewing technical analysis to be at least as important as fundamental analysis.

Menkhoff (1997) investigated the behavior of foreign exchange professionals such as dealers or fund managers in Germany in 1992. His survey revealed that 87% of the dealers placed a weight of over 10% to technical analysis in their decision making. The mean value of the importance of technical analysis appeared to be 35% and other professionals also showed similar responses. Respondents believed that technical analysis influenced their decision from intraday to 2-6 months by giving a weight of between 34% and 40%. Other interesting findings were: (1) professionals preferring technical analysis were younger than other participants; (2) there was no relationship between institutional size and the preferred use of technical analysis; and (3) chartists and fundamentalists both indicated no significant differences in their educational level.

Lui and Mole (1998) surveyed the use of technical and fundamental analysis by foreign exchange dealers in Hong Kong in 1995. The dealers believed that technical analysis was more useful than fundamental analysis in forecasting both trends and turning points. Similar to previous survey results, technical analysis appeared to be important to dealers at the shorter time horizons up to 6 months. Respondents considered moving averages and/or other trend-following systems the most useful technical analysis. The typical length of historical period used by the dealers was 12 months and the most popular data frequency was daily data.

Cheung and Wong (2000) investigated practitioners in the interbank foreign exchange markets in Hong Kong, Tokyo, and Singapore in 1995. Their survey results indicated that about 40% of the dealers believed that technical trading is the major factor determining exchange rates in the medium run (within 6 months), and even in the long run about 17% believed technical trading is the most important determining factor.

Cheung, Chinn, and Marsh (2000) surveyed the views of UK-based foreign exchange dealers on technical anaysis in 1998. In this survey, 33% of the respondents described themselves as technical analysts and the proportion increased by approximately 20% compared to that of five years ago. Moreover, 26% of the dealers responded that technical trading is the most important factor that determines exchange rate movements over the medium run.

Cheung and Chinn (2001) published survey results for US-based foreign exchange traders conducted in 1998. In the survey, about 30% of the traders indicated that technical trading best describes their trading strategy. Five yeas earlier, only 19% of traders had judged technical trading as their trading practice. About 31% of the traders responded that technical trading was the primary factor determining exchange rate movements up to 6 months.

Oberlechner (2001) reported findings from a survey on the importance of technical and fundamental analysis among foreign exchange traders and financial journalists in Frankfurt, London, Vienna, and Zurich in 1996. For foreign exchange traders, technical analysis seemed to be a more important forecasting tool than fundamental analysis up to a 3-month forecasting horizon, while for financial journalists it seemed to be more important up to 1-month. However, forecasting techniques differed in trading locations on shorter forecasting horizons. From intraday to a 3-month forecasting horizon, traders in smaller trading locations (Vienna and Zurich) placed more weight on technical analysis than did traders in larger trading locations (London and Frankfurt). Traders generally used a mixture of both technical and fundamental analysis in their trading practices. Only 3% of the traders exclusively used one of the two forecasting techniques. Finally, comparing the survey results for foreign exchange traders in London to the previous results of Taylor and Allen (1992), the importance of technical analysis appeared to increase across all trading horizons relative to 1988 (the year when Taylor and Allen conducted a survey).

In sum, survey studies indicate that technical analysis has been widely used by practitioners in futures markets and foreign exchange markets, and regarded as an important factor in determining price movements at shorter time horizons. However, no survey evidence for stock market traders was found.

Theory

The Efficient Markets Hypothesis

The efficient markets hypothesis has long been a dominant paradigm in describing the behavior of prices in speculative markets. Working (1949, p. 160) provided an early version of the hypothesis:

> If it is possible under any given combination of circumstances to predict future price changes and have the predictions fulfilled, it follows that the market expectations must have been defective; ideal market expectations would have taken full account of the information which permitted successful prediction of the price changes.

In later work, he revised his definition of a perfect futures market to "… one in which the market price would constitute at all times the best estimate that could be made, from currently available information, of what the price would be at the delivery date of the futures contracts (Working, 1962, p. 446)." This definition of a perfect futures market is in essence identical to the famous definition of an efficient market given by Fama (1970, p. 383): "A market in which prices always 'fully reflect' available information is called 'efficient'." Since Fama's survey study was published, this definition of an efficient market has long served as the standard definition in the financial economics literature.

A more practical definition of an efficient market is given by Jensen (1978, p. 96) who wrote: "A market is efficient with respect to information set q_t if it is impossible to make economic profits by trading on the basis of information set q_t." Since the economic profits are risk-adjusted returns after deducting transaction costs, Jensen's definition implies that market efficiency may be tested by considering the net profits and risk of trading strategies based on information set q_t. Timmermann and Granger (2004, p. 25) extended Jensen's definition by specifying how the information variables in q_t are used in actual forecasting. Their definition is as follows:

> A market is efficient with respect to the information set, q_t, search technologies, S_t, and forecasting models, M_t, if it is impossible to make economic profits by trading on the basis of signals produced from a forecasting model in M_t defined over predictor variables in the information set q_t and selected using a search technology in S_t.[6]

On the other hand, Jensen (1978, p. 97) grouped the various versions of the efficient markets hypothesis into the following three testable forms based on the definition of the information set q_t:

(1) the Weak Form of the Efficient markets hypothesis, in which the information set q_t is taken to be solely the information contained in the past price history of the market as of time t.

(2) the Semi-strong Form of the Efficient markets hypothesis, in which q_t is taken to be all information that is publicly available at time *t*. (This includes, of course, the past history of prices so the weak form is just a restricted version of this.)

(3) the Strong Form of the Efficient markets hypothesis, in which q_t is taken to be all information known to anyone at time *t*.

Thus, technical analysis provides a weak form test of market efficiency because it heavily uses past price history. Testing the efficient markets hypothesis empirically requires more specific

[6] Timmermann and Granger used W_t as a symbol for the information set. The symbol, W_t, has been changed to q_t for consistency.

models that can describe the process of price formation when prices fully reflect available information. In this context, two specific models of efficient markets, the martingale model and the random walk model, are explained next.

The Martingale Model

In the mid-1960s, Samuelson (1965) and Mandelbrot (1966) independently demonstrated that a sequence of prices of an asset is a martingale (or a fair game) if it has unbiased price changes. A martingale stochastic process $\{P_t\}$ is expressed as:

$$E(P_{t+1} \mid P_t, P_{t-1}, \ldots) = P_t, \qquad (1)$$

or equivalently,

$$E(P_{t+1} - P_t \mid P_t, P_{t-1}, \ldots) = 0, \qquad (2)$$

where P_t is a price of an asset at time t. Equation (1) states that tomorrow's price is expected to be equal to today's price, given knowledge of today's price and of past prices of the asset. Equivalently, (2) states that the asset's expected price change (or return) is zero when conditioned on the asset's price history. The martingale process does not imply that successive price changes are independent. It just suggests that the correlation coefficient between these successive price changes will be zero, given information about today's price and past prices. Campbell, Lo, and MacKinlay (1997, p. 30) stated that:

> In fact, the martingale was long considered to be a necessary condition for an efficient asset market, one in which the information contained in past prices is instantly, fully, and perpetually reflected in the asset's current price. If the market is efficient, then it should not be possible to profit by trading on the information contained in the asset's price history; hence the conditional expectation of future price changes, conditional on the price history, cannot be either positive or negative (if short sales are feasible) and therefore must be zero.

Thus, the assumptions of the martingale model eliminate the possibility of technical trading rules based only on price history that have expected returns in excess of equilibrium expected returns. Another aspect of the martingale model is that it implicitly assumes risk neutrality. However, since investors are generally risk-averse, in practice it is necessary to properly incorporate risk factors into the model.

As a special case of the fair game model, Fama (1970) suggested the sub-martingale model, which can be expressed as:

$$E(\tilde{P}_{j,t+1} \mid q_t) \geq P_{j,t}, \text{ or equivalently, } E(\tilde{r}_{j,t+1} \mid q_t) \geq 0. \qquad (3)$$

where $P_{j,t}$ is the price of security j at time t; $P_{j,t+1}$ is its price at $t+1$; $r_{j,t+1}$ is the one-period percentage return $(P_{j,t+1} - P_{j,t})/P_{j,t}$; q_t is a general symbol for whatever set of information is assumed to be "fully reflected" in the price at t: and the tildes indicate that $P_{j,t+1}$ and $r_{j,t+1}$ are random variables at t. This states that the expected value of next period's price based on the information available at time t, q_t, is equal to or greater than the current price. Equivalently, it says that the expected returns and price changes are equal to or greater than zero. If (3) holds as an equality, then the price sequence $\{P_{j,t}\}$ for security j follows a martingale with respect to the information sequence $\{q_t\}$. An important empirical implication of the sub-martingale model is that no trading rules based only on the information set q_t can have greater expected returns than ones obtained by following a buy-and-hold strategy in a future period. Fama (1970, p. 386) emphasized that "Tests of such rules will be an important part of the empirical evidence on the efficient markets model."

Random Walk Models

The idea of the random walk model goes back to Bachelier (1900) who developed several models of price behavior for security and commodity markets.[7] One of his models is the simplest form of the random walk model: if P_t is the unit price of an asset at the end of time *t*, then it is assumed that the increment $P_{t+t} - P_t$ is an independent and normally distributed random variable with zero mean and variance proportional to t. The random walk model may be regarded as an extension of the martingale model in the sense that it provides more details about the economic environment. The martingale model implies that the conditions of market equilibrium can be stated in terms of the first moment, and thus it tells us little about the details of the stochastic process generating returns.

Campbell, Lo, and MacKinlay (1997) summarize various versions of random walk models as the following three models, based on the distributional characteristics of increments. Random walk model 1 (RW1) is the simplest version of the random walk hypothesis in which the dynamics of $\{P_t\}$ are given by the following equation:

$$P_t = m + P_{t-1} + e_t, \qquad e_t \sim IID(0, s^2), \tag{4}$$

where m is the expected price change or drift, and $IID(0, s^2)$ denotes that e_t is independently and identically distributed with mean 0 and variance s^2. The independence of increments e_t implies that the random walk process is also a fair game, but in a much stronger sense than the martingale process: independence implies not only that increments are uncorrelated, but that any nonlinear functions of the increments are also uncorrelated. Fama (1970, p. 386) stated that "In the early treatments of the efficient markets model, the statement that the current price of a security 'fully reflects' available information was assumed to imply that successive price changes (or more usually, successive one-period returns) are independent. In addition, it was usually assumed that successive changes (or returns) are identically distributed." However, the assumption of identically distributed increments has been questioned for financial asset prices over long time spans because of frequent changes in the economic, technological, institutional, and regulatory environment surrounding the asset prices.

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[7] Working (1934) independently developed the idea of a random walk model for price movements. Although he never mentioned the "random walk model," Working suggested that many economic time series resemble a "random-difference series," which is simply a different label for the same statistical model. He emphasized that in the statistical analysis of time series showing the characteristics of the random-difference series in important degree, it is essential for certain purposes to have such a standard series to provide a basis for statistical tests (p. 16), and found that wheat price changes resembled a random-difference series.

Random walk model 2 (RW2) relaxes the assumptions of RW1 to include processes with independent but non-identically distributed increments (e_t):

$$P_t = m + P_{t-1} + e_t, \qquad e_t \sim INID(0, s_t^2). \tag{5}$$

RW2 can be regarded as a more general price process in that, for example, it allows for unconditional heteroskedasticity in the e_t's, a particularly useful feature given the time-variation in volatility of many financial asset return series.

Random walk model 3 (RW3) is an even more general version of the random walk hypothesis, which is obtained by relaxing the independence assumption of RW2 to include processes with dependent but uncorrelated increments. For example, a process that has the following properties satisfies the assumptions of RW3 but not of RW1 and RW2: $Cov[e_t, e_{t-1}] = 0$ for all $k \neq 0$, but where $Cov[e_t^2, e_{t-1}^2] \neq 0$ for some $k \neq 0$. This process has uncorrelated increments but is evidently not independent because its squared increments are correlated.

Fama and Blume (1966) argued that, in most cases, the martingale model and the random walk model are indistinguishable because the martingale's degree of dependence is so small, and hence for all practical purposes they are the same. Nevertheless, Fama (1970) emphasized that market efficiency does not require the random walk model. From the viewpoint of the sub-martingale model, the market is still efficient unless returns of technical trading rules exceed those of the buy-and-hold strategy, even though price changes (increments) in a market indicate small dependence. In fact, the martingale model does not preclude any significant effects in higher order conditional moments since it assumes the existence of the first moment (expected return) only.

Noisy Rational Expectations Models

The efficient markets model implies instantaneous adjustment of price to new information by assuming that the current equilibrium price fully impounds all available information. It implicitly assumes that market participants are rational and they have homogeneous beliefs about information. In contrast, noisy rational expectations equilibrium models assume that the current price does not fully reveal all available information because of noise (unobserved current supply of a risky asset or information quality) in the current equilibrium price. Thus, price shows a pattern of systematic slow adjustment to new information and this implies the existence of profitable trading opportunities.

Noisy rational expectations equilibrium models were developed on the basis of asymmetric information among market participants. Working (1958) first developed a model in which traders are divided into two groups: a large group of well-informed and skillful traders and a small group of ill-informed and unskillful traders. In his model, some traders seek to get pertinent market information ahead of the rest, while others seek information that gives advance indication of future events. Since there exist many different pieces of information that influence prices, price tends to change gradually and frequently. The tendency of gradual price changes results in very short-term predictability. In the process, traders who make their decision on the basis of new information may seek quick profits or take their losses quickly, because they may regard an adverse price movement as a signal that the price is reflecting other information which they do not possess. Meanwhile, ill-qualified traders who have little opportunity to acquire valuable information early and little ability to interpret the information if any may choose to "go with the market."

Smidt (1965b) developed another early model in this area and provided the first theoretical foundation for the possibility of profitable technical trading rules by taking account of the speed and efficiency with which a speculative market responds to new information. He hypothesized two futures markets. The first market is an ideal one where all traders are immediately and simultaneously aware of any new information pertaining to the price of futures contracts. The second market has two types of traders, "insiders" and "outsiders." While insiders are traders who learn about new information relatively early, outsiders are traders who only hear about the new information after insiders have heard about it. According to Smidt, if all traders are equally well informed as in the ideal market or if insiders perfectly predict subsequent outsiders' behavior, there exists only a limited possibility of profits for technical traders. Even if insiders do not always perfectly anticipate outsiders, technical analysis may have no value if insiders are as likely to underestimate as to overestimate the outsiders' response to new information. However, if insiders do not perfectly predict outsiders' behavior and hence there is a systematic tendency for a price rise or fall to be followed by a subsequent further rise or fall, then technical traders may earn long-run profits in a market, even in the absence of price trends. Thus, Smidt argued that "evidence that a trading system generates positive profits that are not simply the results of following a trend also constitutes evidence of market imperfections" (p.130).

Grossman and Stiglitz (1976, 1980) developed a formal noisy rational expectations model in which there is an equilibrium degree of disequilibrium. They demonstrated that, in a competitive market, no one has an incentive to obtain costly information if the market-clearing price reflects all available information, and thus the competitive market breaks down. Like Smidt's framework, Grossman and Stiglitz's model also assumes two types of traders, "informed" and "uninformed," depending on whether they paid a cost to obtain information. When price reflects all available information, each informed trader in a competitive market feels they could stop paying for information and do as well as uninformed traders. But all informed traders feel this way. Therefore, if a market is informationally efficient, then having any positive fraction informed is not an equilibrium. Conversely, having no one informed is also not an equilibrium since each trader feels that they could make profits from becoming informed.

Grossman and Stiglitz further demonstrated that if information is very inexpensive, or if informed traders have very precise information, then equilibrium exists and the speculative market price will reveal most of the informed traders' information. However, such a market will be very thin because it can be made of traders with almost homogeneous beliefs. Grossman and Stiglitz's model supports the weak form of the efficient markets hypothesis in which no profits are made from looking at price history because their model assumes uninformed traders have rational expectations. What is not supported by their model is the strong form of the efficient markets hypothesis because prices are unable to fully reflect all private information and thus the informed do a better job in allocating their portfolio than the uninformed.

In contrast to Grossman and Stiglitz, Hellwig (1982) showed that if the time span between successive market transactions is short, the market can approximate full informational efficiency closely, but the returns to the informed traders can be greater than zero. The Grossman-Stiglitz conclusion resulted from the assumption that traders learn from current prices before any transactions at these prices take place, while Hellwig assumes that traders draw information only from past equilibrium prices at which transactions have actually been completed. Thus, the informed have time to use their information before other traders have inferred it from the market price and can make positive returns, which in turn provide an incentive to spend resources on information.

In Hellwig's model, the market cannot be informationally efficient if traders learn from past prices rather than current prices, because the information contained in the current price is not yet 'correctly evaluated' by uninformed traders. However, the deviation from informational efficiency is small if the period is short, since the underlying stochastic processes are continuous and have only small increments in a short time interval. That is, the news of any one period is insignificant and thus the informational advantage of informed traders is small. This implies that the equilibrium price in any period must be close to an informationally efficient market level. Despite their small informational advantage, however, informed traders can make positive returns by taking very large positions in their transactions. Therefore, the return to being informed in one period is prevented from being zero and the market approaches full informational efficiency.

Treynor and Ferguson (1985) showed that if technical analysis is combined with non-public information that may change the price of an asset, then it could be useful in achieving unusual profit in a speculative market. In their model, an investor obtaining non-public information privately must decide how to act. If the investor receives the information before the market does and establishes an appropriate position, then they can expect a profit from the change in price that is forthcoming when the market receives the information. If the investor receives the information after the market does, then they do not take the position. The investor uses past prices to compute the probability that the market has already incorporated the information. Treynor and Ferguson measured such profitability using Bayes' theorem conditioned on past prices. However, they pointed out that the investor's profit opportunity is created by the non-price information but not the past prices. Past prices only help exploit the information efficiently.

Brown and Jennings (1989) proposed a two-period noisy rational expectations model in which a current (second-period) price is dominated as an informative source by a weighted average of past (first-period) and current prices. According to these authors, if the current price depends on noise (i.e., unobserved current supply of a risky asset) as well as private information of market participants, it cannot be a sufficient statistic for private information. Moreover, noise in the current equilibrium price does not allow for price to fully reveal all publicly available information provided by price histories. Therefore, past prices together with current prices enable investors to make more accurate inferences about past and present signals than do current prices alone. Brown and Jennings demonstrated that technical analysis based on past prices has value in every myopic-investor economy in which current prices are not fully revealing of private information and traders have rational conjectures about the relation between prices and signals.

Grundy and McNichols (1989) independently introduced a multi-period noisy rational expectations model analogous to that in Brown and Jennings (1989). Their model is also similar to the model in Hellwig (1982) in that a sequence of prices fully reveals average private signals $(\bar{Y})$ as the number of rounds of trade becomes infinite, although Hellwig assumed that per capita supply is observable but traders cannot condition their demand on the current price. In Grundy and McNichols' model, supply is unobservable but traders are able to condition their demand on the current price. In particular, they conjectured that when supply is perfectly correlated across rounds, $\bar{Y}$ can be revealed with just two rounds of trade. In the first round of trade, an exogenous supply shock keeps price from fully revealing the average private signal $\bar{Y}$. Allowing a second round of trade leads to one of two types of equilibria: non-$\bar{Y}$-revealing and $\bar{Y}$-revealing. In the non-$\bar{Y}$-revealing equilibrium, traders have homogeneous beliefs concerning the second-round price. Thus, traders do not learn about $\bar{Y}$ from the second round of trade and continue to hold their Pareto-optimal allocations from the first round. The market will again clear at the price of the first round and no trade takes place in the second round. In the $\bar{Y}$-revealing equilibrium, Pareto-optimal allocations are not achieved in the first round and traders do not have concordant beliefs concerning the second-round price, since the sequence of prices, i.e., prices of the first and second rounds, reveals $\bar{Y}$. Traders do not learn $\bar{Y}$ from the second-round price alone but do learn it from the price sequence. Trade thus takes place at both the first and second rounds even without new public (or private) information. In the $\bar{Y}$-revealing equilibrium, rational traders are chartists and their risk-sharing behavior leads to trade.

Blume, Easley, and O'Hara (1994) developed an equilibrium model that emphasizes the informational roles of volume and technical analysis. Unlike previous equilibrium models that considered the aggregate supply of a risky asset as the source of noise, their model assumes that the source of noise is the quality of information. They showed that volume provides "information about the quality of traders' information" that cannot be conveyed by prices, and thus, observing the price and the volume statistics together can be more informative than observing the price statistic alone. In their model, technical analysis is valuable because current market statistics may be insufficient to reveal all information. They argued that "Because the underlying uncertainty in the economy is not resolved in one period, sequences of market statistics can provide information that is not impounded in a single market price" (p. 177). The value of technical analysis depends on the quality of information. Technical analysis can be more valuable if past price and volume data possess higher-quality information, and be less valuable if there is less to be learned from the data. In any case, technical analysis helps traders to correctly update their views on the market.

Noise Traders and Feedback Models

In the early 1990s, several financial economists developed the field of behavioral finance, which is "finance from a broader social science perspective including psychology and sociology" (Shiller 2003, p. 83). In the behavioral finance model, there are two types of investors: arbitrageurs (also called sophisticated investors or smart money) and noise traders (feedback traders or liquidity traders). Arbitrageurs are defined as investors who form fully rational expectations about security returns, while noise traders are investors who irrationally trade on noise as if it were information (Black 1986). Noise traders may obtain their pseudosignals from technical analysts, brokers, or economic consultants and irrationally believe that these signals impound information. The behavioralists' approach, also known as feedback models, is then based on two assumptions. First, noise traders' demand for risky assets is affected by their irrational beliefs or sentiments that are not fully justified by news or fundamental factors. Second, since arbitrageurs are likely to be risk averse, arbitrage, defined as trading by fully rational investors not subject to such sentiment, is risky and therefore limited (Shleifer and Summers 1990, p. 19).

In feedback models, noise traders buy when prices rise and sell when prices fall, like trend chasers. For example, when noise traders follow positive feedback strategies (buy when prices rise), this increases aggregate demand for an asset they purchased and thus results in a further price increase. Arbitrageurs having short horizons may think that the asset is mispriced above its fundamental value, and sell it short. However, their arbitrage is limited because it is always possible that the market will perform very well (fundamental risk) and that the asset will be even more overpriced by noise traders in the near future because they can be even more optimistic ("noise trader risk," De Long et al. 1990a). As long as there exists risk created by the unpredictability of noise traders' opinions, sophisticated investors' arbitrage will be reduced even in the absence of fundamental risk and thus they do not fully counter the effects of the noise traders. Rather, it may be optimal for arbitrageurs to jump on the "bandwagon" themselves. Arbitrageurs optimally buy the asset that noise traders have purchased and sell it out much later when its price rises high enough. Therefore, although ultimately arbitrageurs make prices return to their fundamental levels, in the short run they amplify the effect of noise traders (De Long et al. 1990b). On the other hand, when noise traders are pessimistic and thus follow negative feedback strategies, downward price movement drives further price decreases and over time this process eventually creates a negative bubble. In the feedback models, since noise traders may be more aggressive than arbitrageurs due to their overoptimistic (or overpessimistic) or overconfident views on markets, they bear more risk with higher expected returns. As long as risk-return tradeoffs exist, noise traders may earn higher returns than arbitrageurs. De Long et al. (1991) further showed that even in the long run noise traders as a group survive and dominate the market in terms of wealth despite their excessive risk taking and excessive consumption. Hence, the feedback models suggest that technical trading profits may be available even in the long run if technical trading strategies (buy when prices rise and sell when prices fall) are based on noise or "popular models" and not on information such as news or fundamental factors (Shleifer and Summers 1990).

Other Models

Additional models provide support for the use of technical analysis. Beja and Goldman (1980) introduced a simple disequilibrium model that explained the dynamic behavior of prices in the short run. The rationale behind their model was, "When price movements are forced by supply and demand imbalances which may take time to clear, a nonstationary economy must experience at least some transient moments of disequilibrium. Observed prices will then depend not only on the state of the environment, but also on the state of the market" (p. 236). The state of the economic environment represents agents' endowments, preferences, and information generally changing with time. In the disequilibrium model, therefore, the investor's excess demand function for a security includes two components: (1) fundamental demand which is the aggregate demand that the auctioneer would face if at time *t* one were to conduct a Walrasian auction in the economy; and (2) the difference between actual excess demand and corresponding fundamental demand. With non-equilibrium trading, the demands should reflect the potential for direct speculation on price changes, including the price's adjustment towards equilibrium. In general, this is a function of both speculators' average assessment of the current trend in the security's price and the opportunity growth rate of alternative investments in non-equilibrium trading with comparable securities. The process of trend estimation is adaptive because the price changes include some randomness. Beja and Goldman showed that when trend followers have some market power, an increase in fundamental demand might generate oscillations, although the economy dominated by fundamental demand is stable and non-oscillatory. Furthermore, increasing the market impact of the trend followers causes oscillations and makes the system unstable. These situations imply poor signaling quality of prices. On the other hand, they also demonstrated that moderate speculation might improve the quality of price signal and thus accelerate the convergence to equilibrium. This happens when the speculators' response to changes in price movements is relatively faster than the impact of fundamental demand on price adjustment.

Froot, Scharfstein, and Stein (1992) demonstrated that herding behavior of short-horizon traders can lead to informational inefficiency. Their model showed that an informed trader who wants to buy or sell in the near future could benefit from their information only if it is subsequently impounded into the price by the trades of similarly informed speculators. Thus, short-horizon traders would make profits when they can coordinate their research efforts on the same information. This kind of positive informational spillover can be so powerful that herding traders may even analyze information that is not closely related to the asset's long-run value. Technical analysis is one example. Froot, Scharfstein, and Stein stated, "the very fact that a large number of traders use chartist models may be enough to generate positive profits for those traders who already know how to chart. Even stronger, when such methods are popular, it is optimal for speculators to choose to chart" (p. 1480). In their model, such an equilibrium is possible even in the condition in which prices follow a random walk and hence publicly available information has no value in forecasting future price changes.

Clyde and Osler (1997) provide another theoretical foundation for technical analysis as a method for nonlinear prediction on a high dimension (or chaotic) system. They showed that graphical technical analysis methods might be equivalent to nonlinear forecasting methods using Takens' (1981) method of phase space reconstruction combined with local polynomial mapping techniques for nonlinear prediction. In Takens' method, the true phase space of a dynamic system with *n* state variables can be reconstructed by plotting an observable variable associated with the system against at least 2*n* of its own lagged values (p. 494). The objective of the phase space reconstruction is to discover an attractor, and if an attractor is found, nonlinear prediction can be performed using local polynomial mapping techniques. Forecasting using local polynomial mapping is related to identifying the current position on the attractor and then observing the evolution over time of points near the current point. If points near the current point evolve to points that are near each other on the attractor, forecasting can be made with some confidence that the current point will evolve to the same region.

The above process was tested by applying the identification algorithm of a "head-and-shoulders" pattern to a simulated high-dimension nonlinear price series to see if technical analysis has any predictive power. More specifically, the following two hypotheses were tested: (1) technical analysis has no more predictive power on nonlinear data than it does on random data; and (2) when applied to nonlinear data, technical analysis earns no more hypothetical profits than those generated by a random trading rule. For the first hypothesis, the fraction of total positions that are profitable (the hit ratio) was investigated. The result indicated that the hit ratios exceeded 0.5 in almost all cases when the head-and-shoulders pattern was applied to the nonlinear series. Moreover, profits from applying the head-and-shoulders pattern to the nonlinear series exceeded the median of those from the bootstrap simulated data in almost all cases, even at the longer horizons. Thus, the first hypothesis was rejected. Similarly, the hit ratio tests for 100 nonlinear series also rejected the second hypothesis. As a result, technical analysis seemed to work better on nonlinear data than on random data and generated more profits than random buying and selling when applied to a known nonlinear system. This led Clyde and Osler to conclude that "Technical methods may generally be crude but useful methods of doing nonlinear analysis" (p. 511).

Introducing a simple agent-based model for market price dynamics, Schmidt (1999, 2000, 2002) showed that if technical traders are capable of affecting market liquidity, their concerted actions can move the market price in the direction favorable to their strategy. The model assumes a constant total number of traders that consists of "regular" traders and "technical" traders. Again, the regular traders are partitioned into buyers and sellers, and have two dynamic patterns in their behavior: a "fundamentalist" component and a "chartist" component. The former motivates traders to buy an asset if the current price is lower than the fundamental value, and to sell it otherwise, while the latter leads traders to buy if the price increases and sell when price falls. In the model, price moves linearly with the excess demand, which in turn is proportional to the excess number of buyers from both regular and technical traders.

The result is similar to those of Beja and Goldman (1980) and Froot, Scharfstein, and Stein (1992). In the absence of technical traders, price dynamics formed slowly decaying oscillations around an asymptotic value. However, inclusion of technical traders in the model increased the price oscillation amplitude. The logic is simple: if technical traders believe price will fall, they sell, and thus, excess demand decreases. As a result, price decreases, and the chartist component of regular traders forces them to sell. This leads price to decrease further until the fundamentalist priorities of regular traders become overwhelming. The opposite situation occurs if technical traders make a buy decision based on their analysis. Hence, Schmidt concluded that if technical traders are powerful enough in terms of trading volume, they can move price in the direction favorable to their technical trading strategy.

Summary of Theory

In efficient market models, such as the martingale model and random walk models, technical trading profits are not feasible because, by definition, in efficient markets current prices reflect all available information (Working 1949, 1962; Fama 1970) or it is impossible to make risk-adjusted profits net of all transaction costs by trading on the basis of past price history (Jensen 1978). The martingale model suggests that an asset's expected price change (or return) is zero when conditioned on the asset's price history. In particular, the sub-martingale model (Fama 1970) implies that no trading rules based only on past price information can have greater expected returns than buy-and-hold returns in a future period. The simplest random walk model assumes that successive price changes are independently and identically distributed with zero mean. Thus, the random walk model has much stronger assumptions than the martingale model.

In contrast, other models, such as noisy rational expectations models, feedback models, disequilibrium models, herding models, agent-based models, and chaos theory, postulate that price adjusts sluggishly to new information due to noise, market frictions, market power, investors' sentiments or herding behavior, or chaos. In these models, therefore, there exist profitable trading opportunities that are not being exploited. For example, Brown and Jennings's noisy rational expectations model assumes that the current price does not fully reveal private information because of noise (unobserved current supply of a risky asset) in the current equilibrium price, so that historical prices (i.e., technical analysis) together with the current price help traders make more precise inferences about past and present signals than does the current price alone. As another example, behavioral finance models posit that noise traders, who misperceive noise as if it were information (news or fundamental factors) and irrationally act on their belief or sentiments, bear a large amount of risk relative to rational investors and thus may earn higher expected returns. Since noise trader risk (future resale price risk) limits rational investors' arbitrage even when there is no fundamental risk, noise traders on average can earn higher returns than rational investors in the short run, and even in the long run they can survive and dominate the market (De Long et al. 1990a, 1991). The behavioral models suggest that technical trading may be profitable in the long run even if technical trading strategies (buy when prices rise and sell when prices fall) are based on noise or "popular models" and not on information (Shleifer and Summers 1990).

Nevertheless, the efficient markets hypothesis still seems to be a dominant paradigm in the sense that financial economists have not yet reached a consensus on a better model of price formation. Over the last two decades, however, the efficient markets paradigm has been increasingly challenged by a growing number of alternative theories such as noisy rational expectations models and behavioral models. Hence, sharp disagreement in theoretical models makes empirical evidence a key consideration in determining the profitability of technical trading strategies. Empirical findings regarding technical analysis are reviewed next.

Empirical Studies

Numerous empirical studies have tested the profitability of various technical trading systems, and many of them included implications about market efficiency. In this report, previous empirical studies are categorized into two groups, "early" studies and "modern" studies, based on an overall evaluation of each study in terms of the number of technical trading systems considered, treatments of transaction costs, risk, data snooping problems, parameter optimization and out-of-sample verification, and statistical tests adopted. Most early studies generally examined one or two trading systems and considered transaction costs to compute net returns of trading rules. However, risk was not adequately handled, statistical tests of trading profits and data snooping problems were often disregarded, and out-of-sample verification along with parameter optimization were omitted, with a few exceptions. In contrast, modern studies simulate up to thousands of technical trading rules with the growing power of computers, incorporate transaction costs and risk, evaluate out-of-sample performance of optimized trading rules, and test statistical significance of trading profits with conventional statistical tests or various bootstrap methods.

Although the boundary between early and modern studies is blurred, this report regards Lukac, Brorsen, and Irwin's (1988) work as the first modern study since it was among the first technical trading studies to substantially improve upon early studies in many aspects. They considered 12 technical trading systems, conducted out-of-sample testing for optimized trading rules with a statistical significance test, and measured performance of trading rules after adjusting for transaction costs and risk. Thus, early studies commence with Donchian's (1960) study and include 42 studies through 1987, while modern studies cover the 1988-2004 period with 92 studies.[8] Figure 1 presents the number of technical trading studies over several decades. It is noteworthy that during the last decade academics' interest in technical trading rules has increased dramatically, particularly in stock markets and foreign exchange markets. The number of technical trading studies over the 1995-2004 period amounts to about half of all empirical studies conducted since 1960. In this report, representative studies that contain unique characteristics of each group are reviewed and discussed. The report also includes tables that summarize each empirical study with regard to markets, data frequencies, in- and out-of- sample periods, trading systems, benchmark strategies, transaction costs, optimization, and conclusions.

Technical Trading Systems

Before reviewing historical research, it is useful to first introduce and explicitly define major types of technical trading systems. A technical trading system comprises a set of trading rules that can be used to generate trading signals. In general, a simple trading system has one or two parameters that determine the timing of trading signals. Each rule contained in a trading system is the results of parameterizations. For example, the Dual Moving Average Crossover system with two parameters (a short moving average and a long moving average) may be composed of hundreds of trading rules that can be generated by altering combinations of the two parameters. Among technical trading systems, the most well-known types of systems are moving averages, channels (support and resistance), momentum oscillators, and filters. These systems have been widely used by academics, market participants or both, and, with the exception of filter rules, have been prominently featured in well-known books on technical analysis, such as Schwager (1996), Kaufman (1998), and Pring (2002). Filter rules were exhaustively tested by academics for several decades (the early 1960s through the early 1990s) before moving average systems gained popularity in academic research. This section describes representative trading systems for each major category: Dual Moving Average Crossover, Outside Price Channel (Support and Resistance), Relative Strength Index, and Alexander's Filter Rule.

[8] Modern studies were surveyed through August 2004.

Dual Moving Average Crossover

Moving average based trading systems are the simplest and most popular trend-following systems among practitioners (Taylor and Allen 1992; Lui and Mole 1998). According to Neftci (1991), the (dual) moving average method is one of the few technical trading procedures that is statistically well defined. The Dual Moving Average Crossover system generates trading signals by identifying when the short-term trend rises above or below the long-term trend. Specifications of the system are as follows:

A. Definitions
   1. Shorter Moving Average over *s* days at time t $(SMA_t) = \sum_{i=1}^{s} P_{t-i+1}^{c} / s$, where P_t^c is the close at time *t* and $s < t$.
   2. Longer Moving Average over *l* days at time t $(LMA_t) = \sum_{i=1}^{l} P_{t-i+1}^{c} / l$, where $s < l \leq t$.

B. Trading rules
   1. Go long at P_{t+1}^{o} if $SMA_t > LMA_t$, where P_{t+1}^{o} is the open at time $t+1$.
   2. Go short at P_{t+1}^{o} if $SMA_t < LMA_t$.

C. Parameters: s, l.

Outside Price Channel

Next to moving averages, price channels are also extensively used technical trading methods. The price channel is sometimes referred to as "trading range breakout" or "support and resistance." The fundamental characteristic underlying price channel systems is that market movement to a new high or low suggests a continued trend in the direction established. Thus, all price channels generate trading signals based on a comparison between today's price level with price levels of some specified number of days in the past. The Outside Price Channel system is analogous to a trading system introduced by Donchian (1960), who used only two preceding calendar week's ranges as a channel length. More specifically, this system generates a buy signal anytime the closing price is outside (greater than) the highest price in a channel length (specified time interval), and generates a sell signal anytime the closing price breaks outside (lower than) the lowest price in the price channel. Specifications of the system are as follows:

A. Definitions
   1. Price channel = a time interval including today, *n* days in length.
   2. The Highest High $(HH_t) = \max\{P_{t-1}^{h}, \ldots, P_{t-n+1}^{h}\}$, where P_{t-1}^{h} is the high at time $t-1$.
   3. The Lowest Low $(LL_t) = \min\{P_{t-1}^{l}, \ldots, P_{t-n+1}^{l}\}$, where P_{t-1}^{l} is the low at time $t-1$.

B. Trading rules
   1. Go long at P_t^c if $P_t^c > HH_t$, where P_t^c is the close at time *t*.
   2. Go short at P_t^c if $P_t^c < LL_t$.

C. Parameter: n.

Relative Strength Index

The Relative Strength Index, introduced by Wilder (1978), is one of the most well-known momentum oscillator systems. Momentum oscillator techniques derive their name from the fact that trading signals are obtained from values which "oscillate" above and below a neutral point, usually given a zero value. In a simple form, the momentum oscillator compares today's price with the price of n-days ago. Wilder (1978, p. 63) explains the momentum oscillator as follows:

> The momentum oscillator measures the velocity of directional price movement. When the price moves up very rapidly, as some point it is considered to be overbought; when it moves down very rapidly, at some point it is considered to be oversold. In either case, a reaction or reversal is imminent.

Momentum values are similar to standard moving averages, in that they can be regarded as smoothed price movements. However, since the momentum values generally decrease before a reverse in trend has taken place, momentum oscillators may identify a change in trend in advance, while moving averages usually cannot. The Relative Strength Index was designed to overcome two problems encountered in developing meaningful momentum oscillators: (1) erroneous erratic movement, and (2) the need for an objective scale for the amplitude of oscillators.[9] Specifications of the system are as follows:

A. Definitions
1. Up Closes at time t $(UC_t) = P_t^c - P_{t-1}^c$, if $P_t^c > P_{t-1}^c$. P_t^c is the close at time t.
2. Down Closes at time t $(DC_t) = -(P_t^c - P_{t-1}^c)$, if $P_t^c < P_{t-1}^c$.
3. Average Up Closes over n days at time $t,\ t+1,\ t+2,\ \ldots$:
   $AUC_t = \sum_{i=1}^{n} UC_{t-i+1}/n,\ \ AUC_{t+1} = (AUC_t \times (n-1) + UC_{t+1})/n,$
   $AUC_{t+2} = (AUC_{t+1} \times (n-1) + UC_{t+2})/n,\ \ldots.$
4. Average Down Closes over n days at time $t,\ t+1,\ t+2,\ \ldots$:
   $ADC_t = \sum_{i=1}^{n} DC_{t-i+1}/n,\ \ ADC_{t+1} = (ADC_t \times (n-1) + DC_{t+1})/n,$
   $ADC_{t+2} = (ADC_{t+1} \times (n-1) + DC_{t+2})/n,\ \ldots.$
5. Relative Strength at time t $(RS_t) = AUC_t / ADC_t$.
6. Relative Strength Index at time t $(RSI_t) = 100 - (100/(1+RS_t))$.
7. Entry Thresholds $(ET, 100-ET)$: RSI values beyond which buy or sell signals are generated.

B. Trading rules
1. Go long when RSI falls below ET and rises back above it.
2. Go short when RSI rises above $100-ET$ and falls back below it.

[9] See Wilder (1978) for detailed discussion.

C. Parameters: n, ET.[10]

Alexander's Filter Rule

This system was first introduced by Alexander (1961, 1964) and exhaustively tested by numerous academics until the early 1990s. Since then, its popularity among academics has been replaced by moving average methods. This system generates a buy (sell) signal when today's closing price rises (falls) by x% above (below) its most recent low (high). Moves less than x% in either direction are ignored. Thus, all price movements smaller than a specified size are filtered out and the remaining movements are examined. Alexander (1961, p. 23) argued that "If stock price movements were generated by a trendless random walk, these filters could be expected to yield zero profits, or to vary from zero profits, both positively and negatively, in a random manner." Specifications of the system are as follows:

A. Definitions and abbreviations
   1. High Extreme Point (HEP) = the highest close obtained while in a long trade.
   2. Low Extreme Point (LEP) = the lowest close obtained while in a short trade.
   3. $x =$ the percent filter size.

B. Trading rules
   1. Go long on the close, if today's close rises x% above the LEP.
   2. Go short on the close, if today's close falls x% below the HEP.

C. Parameter: x.

These are only four examples of the very large number of technical trading systems that have been proposed. For other examples, readers should see Wilder (1978), Barker (1981), or other books on technical analysis. In addition, the above examples do not cover other forms of technical analysis such as charting. Most books on technical analysis explain a broad category of visual chart patterns, and some recent academic papers (e.g., Chang and Osler 1999; Lo, Mamaysky, and Wang 2000) have also investigated the forecasting ability of various chart patterns by developing pattern recognition algorithms.

Early Empirical Studies (1960-1987)

Overview

In most early studies, technical trading rules are applied to examine price behavior in various speculative markets, along with standard statistical analyses. Until technical trading rules were dominantly used to test market efficiency, previous empirical studies had employed only statistical analyses such as serial correlation, runs analysis, and spectral analysis. However, these statistical analyses revealed several limitations. As Fama and Blume (1966) pointed out, the simple linear relationships that underlay the serial correlation model were not able to detect the complicated patterns that chartists perceived in market prices. Runs analysis was too inflexible in that a run was terminated whenever a reverse sign occurred in the sequence of successive price changes, regardless of the size of the price change (p. 227). Moreover, it was

[10] Wilder (1978) originally set the parameter values at n = 14 and ET = 30.

difficult to incorporate the elements of risk and transaction costs into statistical analyses. Fama (1970) argued that "there are types of nonlinear dependence that imply the existence of profitable trading systems, and yet do not imply nonzero serial covariances. Thus, for many reasons it is desirable to directly test the profitability of various trading rules" (p. 394). As a result, in early studies technical trading rules are considered as an alternative to avoid such weaknesses of statistical analyses, and are often used together with statistical analyses.

To detect the dependence of price changes or to test the profitability of technical trading rules, early studies used diverse technical trading systems such as filters, stop-loss orders, moving averages, momentum oscillators, relative strength, and channels. Filter rules were the most popular trading system. Although many early studies considered transaction costs to compute net returns of trading rules, few studies considered risk, conducted parameter optimization and out-of-sample tests, or performed statistical tests of the significance of trading profits. Moreover, even after Jensen (1967) highlighted the danger of data snooping in technical trading research, none of the early studies except Jensen and Benington (1970) explicitly dealt with the problem. Technical trading profits were often compared to one of several benchmarks, such as the buy-and-hold returns, geometric mean returns, or zero mean profits, to derive implications for market efficiency.

Among the early studies, three representative studies, Fama and Blume (1966), Stevenson and Bear (1970), and Sweeney (1986), were selected for in-depth reviews. These studies had significant effects on later studies. In addition, these studies contain the aforementioned typical characteristics of early work, but are also relatively comprehensive compared to other studies in the same period. Table 1 presents summaries of each early study in terms of various criteria such as markets studied, data frequencies, sample periods, trading systems, benchmark strategies, transaction costs, optimization, and conclusions.

Representative Early Studies

Fama and Blume (1966), in the best-known and most influential work on technical trading rules in the early period, exhaustively tested Alexander's filter rules on daily closing prices of 30 individual securities in the Dow Jones Industrial Average (DJIA) during the 1956-1962 period. They simulated 24 filters ranging from 0.5% to 50%. Previously, Alexander (1961, 1964) applied his famous filter rules to identify nonlinear patterns in security prices (S&P Industrials, Dow Jones Industrials). He found that the small filter rules generated larger gross profits than the buy-and-hold strategy, and these profits were not likely to be eliminated by commissions. This led him to conclude that there were trends in stock market prices. However, Mandelbrot (1963) pointed out that Alexander's computations of empirical returns included serious biases that exaggerated filter rule profits. Alexander assumed that traders could always buy at a price exactly equal to the subsequent low plus x% and sell at the subsequent high minus x%. Because of the frequency of large price jumps, however, the purchase would occur at a little higher price than the low plus x%, while the sale would occur at somewhat lower price than the high minus x%. By accommodating this criticism, Alexander (1964) re-tested S&P Industrials using the closing prices of the confirmation day as transaction prices. The results indicated that after commissions, only the largest filter (45.6%) beat the buy-and-hold strategy by substantial margin.

Fama and Blume also argued that Alexander's (1961, 1964) results were biased because he did not incorporate dividend payments into data. In general, adjusting for dividends reduces the profitability of short sales and thus decreases the profitability of the filter rules. Thus, Fama and Blume's tests were performed after taking account of the shortcomings of Alexander's works. Their results showed that, when commissions (brokerage fees) were taken into account, only four out of 30 securities had positive average returns per filter. Even ignoring commissions, the filter rules were inferior to a simple buy-and-hold strategy for all but two securities. Fama and Blume split the filter rule returns before commissions into the returns for long and short transactions, respectively. On short transactions, only one security had positive average returns per filter, while on long transactions thirteen securities had higher average returns per filter than buy-and-hold returns. Hence, they argued that even long transaction did not consistently outperform the buy-and-hold strategy.

Fama and Blume went on to examine average returns of individual filters across the 30 securities. When commissions were included, none of the filter rules consistently produced large returns. Although filters between 12% and 25% produced positive average net returns, these were not substantial when compared to buy-and-hold returns. However, when trading positions were broken down into long and short positions, three small filters (0.5%, 1.0%, and 1.5%) generated greater average returns on long positions than those on the buy-and-hold strategy.[11] For example, the 0.5% filter rule generated an average gross return of 20.9% and an average net return of 12.5% after 0.1% clearing house fee per round-trip transaction. The average net return was about 2.5% points higher than the average return (9.86%) of the buy-and-hold strategy. Fama and Blume, however, claimed that the profitable long transactions would not have been better than a simple buy-and-hold strategy in practice, if the idle time of funds invested, operating expenses of the filter rules, and brokerage fees of specialists had been considered. Hence, Fama and Blume concluded that for practical purposes the filter technique could not be used to increase the expected profits of investors.

Stevenson and Bear (1970) conducted a similar study on July corn and soybean futures from 1957 through 1968. They tested three trading systems related to the filter technique: stop-loss orders attributed to Houthakker (1961), filter rules by Alexander and Fama and Blume, and combinations of both rules. The stop-loss order works as follows: an investor buys a futures contract at the opening on the first day of trading and places a stop-loss order *x*% below the purchase price. If the order is not executed, the investor holds the contract until the last possible date prior to delivery. If the order is executed, no further position is assumed until the opening day of trading of the next contract. For each system, three filter sizes (1.5%, 3%, and 5%) were

[11] Dryden (1969) argued that Fama and Blume's results were biased because they assumed that the short rate-of-return for a transaction is simply the negative of the corresponding long rate-of-return. Dryden illustrated this problem with a simple example: "If a transaction is initiated at a price of 100 and concluded at a price of 121, assuming the duration of the transaction is two days, the rate of return is 10% if the filter rule signaled a long transaction, and -11.1% if the transaction is a short one" (p. 322). Thus, the long rate-of-return is always less (absolutely) than the short rate-of-return except in cases that either the total number of days for which the filter had open positions equals one or an opening price equals a closing price. As a result, the rate of return of the buy-and-hold strategy may be overestimated. Dryden argued that about a 20% reduction of Fama and Blume's buy-and-hold rate was appropriate. In this case, additional six filters would have long rates of return in excess of the buy-and-hold rate.

selected and commissions charged were 0.5 cents per bushel for both corn and soybeans. The results indicated that for soybeans the stop-loss order with a 5% filter outperformed a buy-and-hold strategy by a large amount, while for corn it greatly reduced losses relative to the benchmark across all filters. The pure filter systems appeared to have relatively poor performance. For corn, all filters generated negative net returns, although 3% and 5% filters performed better than the buy-and-hold strategy. For soybeans, 1.5% and 3% filters were inferior to the buy-and-hold strategy because they had losses, while a 5% filter rule outperformed the benchmark with positive net returns. The combination system was the best performer among systems. For soybeans, all filters beat the buy-and-hold strategy, and particularly 3% and 5% filters generated large net returns. The 3% and 5% filters also outperformed the buy-and-hold strategy for corn. On the other hand, the combination system against market (counter trend system) indicated nearly opposite results. Overall, stop-loss orders and combination rules were profitable in an absolute sense, outperforming the buy-and-hold strategy. Profits of technical trading rules led Bear and Stevenson to cast considerable doubt on the applicability of the random walk hypothesis to the price behavior of commodity futures markets.

Sweeney (1986) carried out comprehensive tests on various foreign exchange rates by considering risk, transaction costs, post-sample performance, and statistical tests. Based on the assumption that the Capital Asset Pricing Model (CAPM) can explain excess returns to both filter rules and the buy-and-hold strategy and that risk premia are constant over time, Sweeney developed a risk-adjusted performance measure, the so-called X-statistic, in terms of filter returns in excess of buy-and-hold returns. The X-statistic is defined as technical trading returns in excess of buy-and-hold returns plus an adjustment factor which takes account of different risk premia of the two trading strategies. Using the X statistic as a risk-adjusted performance measure, Sweeney tested daily data on the dollar-German mark ($/DM) exchange rate from 1975 through 1980, with filters ranging from 0.5% to 10%. The results indicated that all filters but 10% beat the buy-and-hold strategy and that the X statistic was statistically significant for filters of 0.5% and 1%. The results were mostly retained even after transaction costs of 0.125% per round-trip were considered, with slight reductions in returns (annual mean excess returns of 1.6%-3.7% over the buy-and-hold strategy). Moreover, even when interest-rate differentials in the statistic X were neglected, the results were similar to those of the X-statistic. Indeed, this makes filter tests for foreign exchange rates quite convenient because it is hard to collect the daily interest-rate differentials. As a result, Sweeney additionally tested 10 foreign currencies over the 1973-1980 period, without considering the interest-rate differentials. The time period was divided into two parts, the first 610 days and the remaining 1,220 days. For the first period, the filter rules statistically significantly outperformed the buy-and-hold strategy in 22 out of 70 cases (7 rules for 10 countries). Results for the second period were similar, indicating 21 significant cases. In general, smaller filters (0.5% to 3%) showed better performance than larger filters. Transaction costs affected the results to about the same degree as in the case of the dollar-DM rate.

In Sweeney's model, the CAPM explains returns to the buy-and-hold strategy and the filter rules, and implies that expected excess returns to the filter rule over the buy-and-hold strategy should be equal to zero. Thus, the significant returns of the filter rules suggest that the CAPM cannot explain price behavior in foreign exchange markets. Sweeney concluded that major currency markets indicated serious signs of inefficiency over the first eight years of the generalized managed floating beginning in March 1973. However, he also pointed out that the results could be consistent with the efficient markets hypothesis if risk premia vary over time. In this case, the filter rule on average puts investors into the foreign currency market when the risk premia or the expected returns are larger than average. Then, positive returns on the filter rule may not be true profits but just a reflection of higher average risk borne.

Summary of Early Studies

As summarized in Table 1, early empirical studies examined the profitability of technical trading rules in various markets. The results varied greatly from market to market as the three representative studies indicated. For 30 individual stock markets, Fama and Blume (1966) found that filter rules could not outperform the simple buy-and-hold strategy after transaction costs. For July corn and soybean futures contracts, Stevenson and Bear's (1970) results indicated that stop-loss orders and combination rules of filters and stop-loss orders generated substantial net returns and beat the buy-and-hold strategy. For 10 foreign exchange rates, Sweeney (1986) found that small (long) filter rules generated statistically significant risk-adjusted net returns. Overall, in the early studies, very limited evidence of the profitability of technical trading rules was found in stock markets (e.g., Fama and Blume 1966; Van Horne and Parker 1967; Jensen and Benington 1970), while technical trading rules often realized sizable net profits in futures markets and foreign exchange markets (e.g., for futures markets, Stevenson and Bear 1970; Irwin and Uhrig 1984; Taylor 1986; for foreign exchange markets, Poole 1967; Cornell and Dietrich 1978; Sweeney 1986). Thus, stock markets appeared to be efficient relative to futures markets or foreign exchange markets during the time periods examined.

Nonetheless, the early studies exhibited several important limitations in testing procedures. First, most early studies exhaustively tested one or two popular trading systems, such as the filter or moving average. This implies that the successful results in the early studies may be subject to data snooping (or model selection) problems. Jensen and Benington (1970) argued that "given enough computer time, we are sure that we can find a mechanical trading rule which works on a table of random numbers - provided of course that we are allowed to test the rule on the same table of numbers which we used to discover the rule. We realize of course that the rule would prove useless on any other table of random numbers, and this is exactly the issue with Levy's[12] results" (p. 470). Indeed, Dooly and Shafer (1983) and Tomek and Querin (1984) proved this argument by showing that when technical trading rules were applied to randomly generated price series, some of the series could be occasionally profitable by chance. Moreover, popular trading systems may be ones that have survivorship biases.[13] Although Jensen (1967) suggested replicating the successful results on additional bodies of data and for other time periods to judge the impact of data snooping, none of the early studies except Jensen and Benington (1970) followed this suggestion.

Second, the riskiness of technical trading rules was often ignored. If investors are risk averse, they will always consider the risk-return tradeoffs of trading rules in their investment. Thus, large trading rule returns do not necessarily refute market efficiency since returns may be

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[12] Levy (1967a) showed that some relative strength rules outperformed a benchmark of the geometric average.

[13] Problems caused by the survivorship biases will be discussed in the next section.

improved by taking greater risks. For the same reason, when comparing between trading rule returns and benchmark returns, it is necessary to make explicit allowance for difference of returns due to different degrees of risk. Only a few studies (Jensen and Benington 1970; Cornell and Dietrich 1978; Sweeney 1986) adopted such a procedure.

Third, most early studies lacked statistical tests of technical trading profits. Only four studies (James 1968; Peterson and Leuthold 1982; Bird 1985; Sweeney 1986) measured statistical significance of returns on technical trading rules using Z- or t-tests under the assumption that trading rule returns are normally distributed. However, applying conventional statistical tests to trading rule returns may be invalid since a sequence of trading rule returns generally does not follow the normal distribution. Talyor (1985) argued that "the distribution of the return from a filter strategy under the null hypothesis of an efficient market is not known, so that proper significance tests are impossible" (p. 727). In fact, Lukac and Brorsen (1990) found that technical trading returns were positively skewed and leptokurtic, and thus argued that past applications of t-tests to technical trading returns might be biased. Moreover, in the presence of data snooping, significance levels of conventional hypothesis tests are exaggerated (Lovell 1983; Denton 1985).

Fourth, Taylor (1986, p. 201) argued that "Most published studies contain a dubious optimization. Traders could not guess the best filter size (g) in advance and it is unlikely an optimized filter will be optimal in the future. The correct procedure is, of course, to split the prices. Then choose g using the first part and evaluate this g upon the remaining prices." If the optimal parameter performs well over in- and out-of-sample data, then the researcher may have more confidence in the results. Only three studies (Irwin and Uhrig 1984; Taylor 1983, 1986) used this procedure.

Fifth, technical trading profits were often compared to the performance of a benchmark strategy to derive implications for market efficiency. Benchmarks used in early studies were buy-and-hold returns, geometric mean returns, interest rates for bank deposit, or zero mean profits. However, there was no consensus on which benchmark should be used for a specific market.

Finally, the results of the technical trading studies in the earlier period seem to be difficult to interpret because the performance of trading rules was often reported in terms of an "average" across all trading rules or all assets (i.e., stocks, currencies, or futures contracts) considered, rather than best-performing rules or individual securities (or exchange rates or contracts). For example, in interpreting their results, Fama and Blume (1966) relied on average returns across all filters for a given stock or across all stocks for a given filter. If they evaluated the performance of the best rules or each individual stock, then their conclusion might have been different. Sweeney (1988) pointed out that "The averaging presumably reduces the importance of aberrations where a particular filter works for a given stock as a statistical fluke. The averaging can, however, serve to obscure filters that genuinely work for some but not all stocks" (p. 296).

Modern Empirical Studies (1988-2004)

Overview

As noted previously, "modern" empirical studies are assumed to commence with Lukac, Brorsen, and Irwin (1988), who provide a more comprehensive analysis than any early study. Although modern studies generally have improved upon the limitations of early studies in their testing procedures, treatment of transaction costs, risk, parameter optimization, out-of-sample tests, statistical tests, and data snooping problems still differ considerably among them. Thus, this report categorizes all modern studies into seven groups by reflecting the differences in testing procedures. Table 2 provides general information about each group. "Standard" refers to studies that included parameter optimization and out-of-sample tests, adjustment for transaction cost and risk, and statistical tests. "Model-based bootstrap" studies are ones that conducted statistical tests for trading returns using a model-based bootstrap approach introduced by Brock, Lakonishok, and LeBaron (1992). "Genetic programming" and "Reality Check" indicate studies that attempted to solve data snooping problems using the genetic programming technique introduced by Koza (1992) and the Bootstrap Reality Check methodology developed by White (2000), respectively. "Chart patterns" refers to studies that developed and applied recognition algorithms for chart patterns. "Nonlinear" studies are those that applied nonlinear methods such as artificial neural networks or feedforward regressions to recognize patterns in prices or estimate the profitability of technical trading rules. Finally, "Others" indicates studies that do not belong to any categories mentioned above.

Modern studies, which are summarized in Tables 3 to 9, include 92 studies dating from Lukac, Brorsen, and Irwin (1988) through Sapp (2004). As with the early studies, a representative study from each of the seven categories is reviewed in detail. They are Lukac, Brorsen, and Irwin (1988), Brock, Lakonishok, and LeBaron (1992), Allen and Karjalainen (1999), Sullivan, Timmermann, and White (1999), Chang and Osler (1999), Gençay (1998a), and Neely (1997).

Representative Modern Studies

Standard Studies

Studies in this category incorporate transaction costs and risk into testing procedures while considering various trading systems. Trading rules are optimized in each system based on a specific performance criterion and out-of-sample tests are conducted for the optimal trading rules. In particular, the parameter optimization and out-of-sample tests are significant improvements over early studies, because these procedures are close to actual traders' behavior and may partially address data snooping problems (Jensen 1967; Taylor 1986).

A representative study among the standard studies is Lukac, Brorsen, and Irwin (1988). Based on the efficient markets hypothesis and the disequilibrium pricing model suggested by Beja and Goldman (1980), they proposed three testable hypotheses: the random walk model, the traditional test of efficient markets, and the Jensen test of efficient markets. Each test was performed to check whether the trading systems could produce positive gross returns, returns above transaction costs, and returns above transaction costs plus returns to risk. Over the 1975-1984 period, twelve technical trading systems were simulated on price series from 12 futures markets across commodities, metals and financials. The 12 trading systems consisted of channels, moving averages, momentum oscillators, filters (or trailing stops), and a combination system, some of which were known to be widely used by fund managers and traders. The nearby contracts were used to overcome the discontinuity problem of futures price series. That is, the current contract is rolled over to the next contract prior to the first notice date and a new trading signal is generated using the past data of the new contract. Technical trading was simulated over the previous three years and parameters generating the largest profit over the period were used for the next year's trading. At the end of the next year, new parameters were again optimized, and so on.[14] Therefore, the optimal parameters were adaptive and the simulation results were out-of-sample. Two-tailed t-tests were performed to test the null hypothesis that gross returns generated from technical trading are zero, while one-tailed t-tests were conducted to test the statistical significance of net returns after transaction costs. In addition, Jensen's a was measured by using the capital asset pricing model (CAPM) to determine whether net returns exist above returns to risk. Results of normality tests indicated that, for aggregate monthly returns from all twelve systems, normality was not rejected and the returns showed negative autocorrelation. Thus, t-tests for portfolio returns were regarded as an appropriate procedure.

The results of trading simulations showed that seven of twelve systems generated statistically significant monthly gross returns. In particular, four trading systems, the close channel, directional parabolic, MII price channel, and dual moving average crossover, yielded statistically significant monthly portfolio net returns ranging from 1.89% to 2.78% after deducting transaction costs.[15] The corresponding return of a buy-and-hold strategy was -2.31%. Deutschmark, sugar, and corn markets appeared to be inefficient because in these markets significant net returns across various trading systems were observed. Moreover, estimated results of the CAPM indicated that the aforementioned four trading systems had statistically significant intercepts (Jensen's a) and thus implied that trading profits from the four systems were not a compensation for bearing systematic risk during the sample period. Thus, Lukac, Brorsen, and Irwin construed that there might be additional causes of market disequilibrium beyond transaction costs and risk. They concluded that the disequilibrium model could be considered a more appropriate model to describe the price movements in the futures markets for the 1978-1984 period.

Other studies in this category are summarized in Table 3. Lukac and Brorsen (1990) used similar procedures to those in Lukac, Brorsen, and Irwin (1988), but extended the number of systems, commodities, and test periods. They investigated 30 futures markets with 23 technical trading systems over the 1975-1986 period. They also used dominant contracts as in Lukac,

[14] Because of this three-year re-optimization method, the out-of-sample period in Lukac, Brorsen, and Irwin's work was from 1978-1984.

[15] These returns are based on the total investment method in which total investment was composed of a 30% initial investment in margins plus a 70% reserve for potential margin calls. The percentage returns can be converted into simple annual returns (about 3.8%-5.6%) by a straightforward arithmetic manipulation.

Brorsen, and Irwin (1988), but skipped trading in months in which a more distant contract was consistently dominant in order to reduce liquidity costs. Parameters were re-optimized by cumulative methods. That is, in each year optimal parameters were selected by simulating data from 1975 to the current year. The parameter producing the largest profit over the period was used for the next year's trading. They found that aggregate portfolio returns of the trading systems were normally distributed, but market level returns were positively skewed and leptokurtic. Thus, they argued that past research that used t-tests on individual commodity returns might be biased. The results indicated that 7 out of 23 trading systems generated monthly net returns above zero at a 10 percent significance level after transaction costs were taken into account. However, most of the profits from the technical trading rules appeared to be made during the 1979-1980 period. In the individual futures markets, exchange rate futures earned highest returns, while livestock futures had the lowest returns.

Most studies in this category, with a few exceptions, investigated foreign exchange markets. Taylor and Tari (1989), Taylor (1992, 1994), Silber (1994), and Szakmary and Mathur (1997) all showed that technical trading rules could yield annual net returns of 2%-10%[16] for major currency futures markets from the late 1970s to the early 1990s. Similarly, Menkoff and Schlumberger (1995), Lee and Mathur (1996a, 1996b), Maillet and Michel (2000), Lee, Gleason, and Mathur (2001), Lee, Pan, and Liu (2001), and Martin (2001) found that technical trading rules were profitable for some spot currencies in each sample period they considered. However, technical trading profits in currency markets seem to gradually decrease over time. For example, Olson (2004) reported that risk-adjusted profits of moving average crossover rules for an 18-currency portfolio declined from over 3% between the late 1970s and early 1980s to about zero percent in the late 1990s. Kidd and Brorsen (2004) provide some evidence that the reduction in returns to managed futures funds in the 1990s, which predominantly use technical analysis, may have been caused by structural changes in markets, such as a decrease in price volatility and an increase in large price changes occurring while markets are closed. For the stock market, Taylor (2000) investigated a wide variety of US and UK stock indices and individual stock prices, finding an average breakeven one-way transaction cost of 0.35% across all data series. In particular, for the DJIA index, an optimal trading rule (a 5/200 moving average rule) estimated over the 1897-1968 period produced a breakeven one-way transaction cost of 1.07% during the 1968-1988 period. Overall, standard studies indicate that technical trading rules generated statistically significant economic profits in various speculative markets, especially in foreign exchange markets and futures markets. Despite the successful results of standard studies, there still exists a possibility that they were spurious because of data snooping problems. Although standard studies optimized trading rules and traced the out-of-sample performance of the optimal trading rules, a researcher can obtain a successful result by deliberately searching for profitable choice variables, such as profitable "families" of trading systems, markets, in-sample estimation periods, out-of-sample periods, and trading model assumptions including performance criteria and transaction costs.

Model-based Bootstrap Studies

Studies in this category apply a model-based bootstrap methodology to test statistical significance of trading profits. Although some other recent studies of technical analysis use the

[16] These are unlevered returns.

bootstrap procedure, model-based bootstrap studies differ from other studies in that they usually analyzed the same trading rules (the moving average and the trading range break-out) that Brock, Lakonishok, and LeBaron investigated, without conducting trading rule optimization and out-of-sample verification. Among modern studies, one of the most influential works on technical trading rules is therefore Brock, Lakonishok, and LeBaron (1992). The reason appears to be their use of a very long price history and, for the first time, model-based bootstrap methods for making statistical inferences about technical trading profits. Brock, Lakonishok, and LeBaron recognized data snooping biases in technical trading studies and attempted to mitigate the problems by (1) selecting technical trading rules that had been popular over a very long time; (2) reporting results from all their trading strategies; (3) utilizing a very long data series; and (4) emphasizing the robustness of results across various non-overlapping subperiods for statistical inference (p. 1734).

According to Brock, Lakonishok, and LeBaron, there are several advantages of using the bootstrap methodology. First, the bootstrap procedure makes it possible to perform a joint test of significance for different trading rules by constructing bootstrap distributions. Second, the traditional t-test assumes normal, stationary, and time-independent distributions of data series. However, it is well known that the return distributions of financial assets are generally leptokurtic, autocorrelated, conditionally heteroskedastic, and time varying. Since the bootstrap procedure can accommodate these characteristics of the data using distributions generated from a simulated null model, it can provide more powerful inference than the t-test. Third, the bootstrap method also allows estimation of confidence intervals for the standard deviations of technical trading returns. Thus, the riskiness of trading rules can be examined more rigorously.

The basic approach in a bootstrap procedure is to compare returns conditional on buy (or sell) signals from the original series to conditional returns from simulated comparison series generated by widely used models for stock prices. The popular models used by Brock, Lakonishok, and LeBaron were a random walk with drift, an autoregressive process of order one (AR (1)), a generalized autoregressive conditional heteroskedasticity in-mean model (GARCH-M), and an exponential GARCH (EGARCH). The random walk model with drift was simulated by taking returns (logarithmic price changes) from the original series and then randomly resampling them with replacement. In other models (AR (1), GARCH-M, EGARCH), parameters and residuals were estimated using OLS or maximum likelihood, and then the residuals were randomly resampled with replacement. The resampled residuals coupled with the estimated parameters were then used to generate a simulated return series. By constraining the starting price level of the simulated return series to be exactly as its value in the original series, the simulated return series could be transformed into price levels. In this manner, 500 bootstrap samples were generated for each null model, and each technical trading rule was applied to each of the 500 bootstrap samples. From these calculations, the empirical distribution for trading returns under each null model was estimated. The null hypothesis was rejected at the a percent level if trading returns from the original series were greater than the a percent cutoff level of the simulated trading returns under the null model.

Brock, Lakonishok, and LeBaron tested two simple technical trading systems, a moving average-oscillator and a trading range breakout (resistance and support levels), on the Dow Jones Industrial Average (DJIA) from 1897 through 1986. In moving average rules, buy and sell signals are generated by two moving averages: a short-period average and a long-period average. More specifically, a buy (sell) position is taken when the short-period average rises above (falls below) the long-period average. Five popular combinations of moving averages (1/50, 1/150, 5/150, 1/200, and 2/200, where the first figure represents the short period and the second figure does the long period) were selected with and without a 1% band and these rules were tested with and without a 10-day holding period for a position. A band around the moving average is designed to eliminate "whipsaws" that occur when the short and long moving averages move closely. In general, introducing a band reduces the number of trades and therefore transaction costs. Moving average rules were divided into two groups depending on the presence of the 10-day holding period: variable-length moving average (VMA) and fixed-length moving average (FMA). FMA rules have fixed 10-day holding periods after a crossing of the two moving averages, while VMA rules do not. Trading range breakout (TRB) rules generate a buy (sell) signal when the current price penetrates a resistance (support) level, which is a local maximum (minimum) price. The local maximums and minimums were computed over the past 50, 150, and 200 days, and each rule was tested with and without a 1% band. With a 1% band, trading signals were generated when the price level moved above (below) the local maximum (minimum) by 1%. For trading range breakout rules, 10-day holding period returns following trading signals were computed. Transaction costs were not taken into account.

Results for the VMA rules indicated that buy returns were all positive with an average daily return of 0.042% (about 12% per year), while sell returns were all negative with an average daily return of -0.025% (about -7% per year). For buy returns, six of the ten rules rejected the null hypothesis that the returns equal the unconditional returns (daily 0.017%), at the 5% significance level using two-tailed t-tests. The other four rules were marginally significant. For sell returns, t-statistics were all highly significant. All the buy-sell spreads were positive with an average of 0.067%, and the t-statistics for these differences were highly significant, rejecting the null hypothesis of equality with zero. The 1% band increased the spread in every case. For the FMA rules, all buy returns were greater than the unconditional 10-day return with an average of 0.53%. Sell returns were all negative with an average of -0.40%. The buy-sell differences were positive for all trading rules with an average of 0.93%. Seven of the ten rules rejected the null hypothesis that the difference equals zero at the 5% significance level. For the trading range breakout rules, buy returns were positive across all the rules with an average of 0.63%, while sell returns were all negative with an average of -0.24%. The average buy-sell return was 0.86% and all six rules rejected the null hypothesis of the buy-sell spread differences being equal to zero.

The bootstrap results showed that all null models could not explain the differences between the buy and sell returns generated by the technical trading rules. For example, the GARCH-M generated the largest buy-sell spread (0.018%) for the VMA rules among the null models, but the spread was still smaller than that (0.067%) from the original Dow series. Similar results were obtained from the FMA and TRB rules. Standard deviations for buys and sells from the original Dow series were 0.89 and 1.34%, respectively, and thus the market was less volatile during buy periods relative to sell periods. Since the buy signals also earned higher mean returns than the sell signals, these results could not be explained by the risk-return tradeoff. Brock, Lakonishok, and LeBaron concluded their study by writing, "the returns-generating process of stocks is probably more complicated than suggested by the various studies using linear models. It is quite possible that technical rules pick up some of the hidden patterns" (p. 1758).

Despite its contribution to the statistical tests in the technical trading literature, Brock, Lakonishok, and LeBaron's study has several shortcomings in testing procedures. First, only gross returns of each trading rule were calculated without incorporating transaction costs, so that no evidence about economic profits was presented. Second, trading rule optimization and out-of-sample tests were not conducted. As discussed in the previous section, these procedures may be important ingredients in determining the genuine profitability of technical trading rules. Finally, results may have been "contaminated" by data snooping problems. Since moving average and trading range breakout rules have kept their popularity over a very long history, these rules were likely to have survivorship biases. If a large number of trading rules are tested over time, some rules may work by pure chance even though they do not possess real predictive power for returns. Of course, inference based on the subset of the surviving trading rules may be misleading because it does not account for the full set of initial trading rules (Sullivan, Timmermann, and White 1999, p. 1649).[17]

Table 4 presents summaries of other model-based bootstrap studies. As indicated in the table, a number of studies in this category either tested the same trading rules as in Brock, Lakonishok, and LeBaron (1992) or followed their testing procedures. For example, Levich and Thomas (1993) tested two popular technical trading systems, filter rules and moving average crossover systems, on five currency futures markets (the Deutsche mark, Japanese yen, British pound, Canadian dollar, and Swiss franc) during the period 1976-1990. To measure the significance level of profits obtained from the trading rules, they constructed the empirical distribution of trading rule profits by randomly resampling price changes in the original series 10,000 times and then applying the trading rules to each simulated series. They found that, across trading rules from both trading systems, average profits of all currencies except the Canadian dollar were substantial (about 6% to 9%) and statistically significant, even after deducting transaction costs of 0.04% per one-way transaction.

Bessembinder and Chan (1998) evaluated the same 26 technical trading rules as in Brock, Lakonishok, and LeBaron (1992) on dividend-adjusted DJIA data over the period 1926-1991. As Fama and Blume (1966) pointed out, incorporating dividend payments into data tends to reduce the profitability of short sales and thus may decrease the profitability of technical trading rules. Bessembinder and Chan also argued that "Brock et al. do not report any statistical tests that pertain to the full set of rules. Focusing on those rules that are ex post most (or least) successful would also amount to a form of data snooping bias" (p. 8). This led them to evaluate

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[17] The following parable on the testing of coin-flipping abilities provided by Merton (1987, p. 104) clarifies this problem. "Some three thousand students have taken my finance courses over the years, and suppose that each had been asked to keep flipping a coin until tails comes up. At the end of the experiment, the winner, call her A, is the person with the longest string of heads. Assuming no talent, the probability is greater than a half that A will have flipped 12 or more straight heads. As the story goes, there is a widely believed theory that no one has coin-flipping ability, and, hence, a researcher is collecting data to investigate this hypothesis. Because one would not expect everyone to have coin-flipping ability, he is not surprised to find that a number of tests failed to reject the null hypothesis. Upon hearing of A's feat (but not of the entire environment in which she achieved it), the researcher comes to MIT where I certify that she did, indeed, flip 12 straight heads. Upon computing that the probability of such an event occurring by chance alone is 2^{-12}, or .00025, the researcher concludes that the widely believed theory of no coin-flipping ability can be rejected at almost any confidence level."

the profitability and statistical significance of returns on portfolios of the trading rules as well as returns on individual trading rules. For the full sample period, the average buy-sell differential across all 26 trading rules was 4.4% per year (an average break-even one-way transaction cost[18] of 0.39%) with a bootstrap p-value of zero. Nonsynchronous trading with a one-day lag reduced the differential to 3.2% (break-even one-way transaction costs of 0.29%) with a significant bootstrap p-value of 0.002. However, the average break-even one-way transaction cost has declined over time, and, for the most recent subsample period (1976-1991) it was 0.22%, which was compared to estimated one-way transaction costs of 0.24%-0.26%.[19] Hence, Bessembinder and Chan concluded that, although the technical trading rules used by Brock, Lakonishok, and LeBaron revealed some forecasting ability, it was unlikely that traders could have used the trading rules to improve returns net of transaction costs.

The results of the model-based bootstrap studies varied enormously across markets and sample periods tested. In general, for (spot or futures) stock indices in emerging markets, technical trading rules were profitable even after transaction costs (Bessembinder and Chan 1995; Raj and Thurston 1996; Ito 1999; Ratner and Leal 1999; Coutts and Cheung 2000; Gunasekarage and Power 2001), while technical trading profits on stock indices in developed markets were negligible after transaction costs or have decreased over time (Hudson, Dempsey, and Keasey 1996; Mills 1997; Bessembinder and Chan 1998; Ito 1999; Day and Wang 2002). For example, Ratner and Leal (1999) documented that Brock, Lakonishok, and LeBaron's moving average rules generated statistically significant net returns in four equity markets (Mexico, Taiwan, Thailand, and the Philippines) over the1982-1995 period. For the FT30 index in the London Stock Exchange, Mills (1997) showed that mean daily returns produced from moving average rules were much higher (0.081% and 0.097%) than buy-and-hold returns for the 1935-1954 and 1955-1974 periods, respectively, although the returns were insignificantly different from a buy-and-hold return for the 1975-1994 period. On the other hand, LeBaron (1999), Neely (2002), and Saacke (2002) reported the profitability of moving average rules in currency markets. For example, LeBaron (1999) found that for the mark and yen, a 150 moving average rule generated Sharpe ratios of 0.60-0.98 after a transaction cost of 0.1% per round-trip over the 1979-1992 period. These Sharpe ratios were much greater than those (0.3-0.4) for buy-and-hold strategies on aggregate US stock portfolios. However, Kho (1966) and Sapp (2004) showed that trading rule profits in currency markets could be explained by time-varying risk premia using some version of the conditional CAPM. In addition, there has been serious disagreement about the source of technical trading profits in the foreign exchange market. LeBaron (1999) and Sapp (2004) reported that technical trading returns were greatly reduced after active intervention periods of the Federal Reserve were eliminated, while Neely (2002) and Saacke (2002) showed that trading returns were uncorrelated with foreign exchange interventions of central banks. Most studies in this category have similar problems to those in Brock, Lakonishok, and LeBaron (1992). Namely, trading rule optimization, out-of-sample

[18] Break-even one-way transaction costs are defined as the percentage one-way trading costs that eliminate the additional return from technical trading (Bessembinder and Chan, 1995, p. 277). They can be calculated by dividing the difference between portfolio buy and sell means by twice the average number of portfolio trades.

[19] This result contrasts sharply with that of Taylor (2000), who found a break-even one-way transaction cost of 1.07% for the DJIA data during the 1968-1988 period using an optimized moving average rule.

verification, and data snooping problems were not seriously considered, although several recent studies incorporated parameter optimization and transaction costs into their testing procedures.

Genetic Programming Studies

Genetic programming, introduced by Koza (1992), is a computer-intensive search procedure for problems based on the Darwinian principle of survival of the fittest. In this procedure, a computer randomly generates a set of potential solutions for a specific problem and then allows them to evolve over many successive generations under a given fitness (performance) criterion. Solution candidates (e.g., technical trading rules) that satisfy the fitness criterion are likely to reproduce, while ones that fail to meet the criterion are likely to be replaced. The solution candidates are represented as hierarchical compositions of functions like tree structures in which the successors of each node provide the arguments for the function identified with the node. The terminal nodes without successors include the input data, and the entire tree structure as a function is evaluated in a recursive manner by investigating the root node of the tree. The structure of the solution candidates, which is not pre-specified as a set of functions, can be regarded as building blocks to be recombined by genetic programming.

When applied to technical trading rules, the building blocks consist of various functions of past prices, numerical and logical constants, and logical functions that construct more complicated building blocks by combining simple ones. The function set can be divided into two groups of functions: real and Boolean. The real-valued functions are arithmetic operators (plus, minus, times, divide), average, maximum, minimum, lag, norm, and so on, while Boolean functions include logical functions (and, or, not, if-then, if-then-else) and comparisons (greater than, less than). There are also real constants and Boolean constants (true or false). As a result, these functions require the trading systems tested to be well defined.

The aforementioned unique features of genetic programming may provide some advantages relative to traditional studies with regard to testing technical trading rules. Traditional technical trading studies investigate a pre-determined parameter space of trading systems, whereas the genetic programming approach examines a search space composed of logical combinations of trading systems or rules. Thus, the fittest or optimized rule identified by genetic programming can be regarded as an ex ante rule in the sense that its parameters are not determined before the test. Since the procedure makes researchers avoid much of the arbitrariness involved in selecting parameters, it can substantially reduce the risk of data snooping biases. Of course, it cannot completely eliminate all potential bias because in practice its search domain (i.e., trading systems) is still constrained to some degree (Neely, Weller, and Dittmar 1997).

Allen and Karjalainen (1999) applied the genetic programming approach to the daily S&P 500 index from 1928-1995 to test the profitability of technical trading rules. They built the following algorithm to find the fittest trading rules (p. 256):

> Step 1. Create a random rule. Compute the fitness of the rule as the excess return in the training period above the buy-and-hold strategy. Do this 500 times (this is the initial population).

Step 2. Apply the fittest rule in the population to the selection period and compute the excess return. Save this rule as the initial best rule.

Step 3. Pick two parent rules at random, using a probability distribution skewed towards the best rule. Create a new rule by breaking the parents apart randomly and recombining the pieces (this is a crossover). Compute the fitness of the new rule in the training period. And then replace one of the old rules by the new rule, using a probability distribution skewed towards the worst rule. Do this 500 times to create a new generation.

Step 4. Apply the fittest (best) rule in the new generation to the selection period and compute the excess return. If the excess return improves upon the previous best rule, save as the new best rule. Stop if there is no improvement for 25 generations or after a total of 50 generations. Otherwise, go back to Step 3.

This procedure describes one trial, and each trial starting from a different random population generates one best rule. The best rule is then tested in the validation (out-of-sample) period immediately following the selection period. If no rule better than the buy-and-hold strategy in the training period is produced in the maximum number of generations, the trial is discarded. In Allen and Karjalainen's study, the size of the genetic structures was bounded to 100 nodes and to a maximum of ten levels of nodes. The search space as building blocks was also constrained to logical combinations of simple rules, which are moving averages and maxima and minima of past prices.

The data used was the S&P 500 index over the 1928-1995 period. To identify optimal trading rules, 100 independent trials were conducted by saving one rule from each trial. The fitness criterion was maximum excess return over the buy-and-hold strategy after taking account of transaction costs. The excess returns were calculated only on buy positions with several one-way transaction costs (0.1%, 0.25%, and 0.5%). To avoid potential data snooping in the selection of time periods, ten successive training periods were employed. The 5-year training and 2-year selection periods began in 1929 and were repeated every five years until 1974, with each out-of-sample test beginning in 1936, 1941, and so on, up to 1981. For example, the first training period was from 1929-1933, the selection period from 1934-1935, and the test period from 1936-1995. For each of the ten training periods, ten trials were executed. The out-of-sample results indicated that trading rules optimized by genetic programming failed to generate consistent excess return after transaction costs. After considering the most reasonable transaction costs of 0.25%, average excess returns were negative for nine of the ten periods. Even after transaction costs of 0.1%, the average excess returns were negative for six out of the ten periods. For most test periods, only a few trading rules indicated positive excess returns. However, in most of the training periods, the optimized trading rules showed some forecasting ability because the difference between average daily returns during days in the market and out of the market was positive, and the volatility during 'in' days was generally lower than during 'out' days. Allen and Karjalainen tried to explain the volatility results by the negative relationship between ex post stock market returns and unexpected changes in volatility. For example, when volatility is higher than expected, investors revise their volatility forecasts upwards, requiring higher expected returns in the future, or lower stock prices and hence lower realized returns at present. It is interesting that these results are analogous to Brock, Lakonishok, and LeBaron's finding (1992).

The structure of the optimal trading rules identified by genetic programming varied across different trials and transaction costs. For instance, with 0.25% transaction costs the most optimal rules were similar to a 250-day moving average rule, while with 0.1% transaction costs approximately half of the rules resembled a rule comparing the normalized price to a constant, and the rest of the rules were similar to either 10- to 40-day moving average rules or a trading range breakout rule comparing today's price to a 3-day minimum price. However, the optimal trading rules in several training periods were too complex to be matched with simple technical trading rules. Overall, throughout the out-of-sample simulations, the genetically optimized trading rules did not realize excess returns over a simple buy-and-hold strategy after transaction costs. Hence, Allen and Karjalainen concluded that their results were generally consistent with market efficiency.

Table 5 presents summaries of other genetic programming studies. Using similar procedures to those used in Allen and Karjalainen (1999), Neely, Weller, and Dittmar (1997) investigated six foreign exchange rates (mark, yen, pound, Swiss franc, mark/yen, and pound/Swiss franc) over the 1974-1995 period. For all exchange rates, they used 1975-1977 as the training period, 1978-1980 as the selection period, and 1981-1995 as the validation period. They set transaction costs of 0.1% per round-trip in the training and selection periods, and 0.05% in the validation period. Results indicated that average annual net returns from each portfolio of 100 optimal trading rules for each exchange rate ranged 1.0%-6.0%. Trading rules for all currencies earned statistically significant positive net returns that exceeded the buy-and-hold returns. In addition, when returns were measured using a median portfolio rule in which a long position was taken if more than 50 rules signaled long and a short position otherwise, net returns in the dollar/mark, dollar/yen, and mark/yen were substantially increased. Similar results were obtained for the Sharpe ratio criterion. However, in many cases the optimal trading rules appeared to be too complex to simplify their structures. The trading rule profits did not seem to be compensation for bearing systematic risk, since most of the betas estimated for four benchmarks (the Morgan Stanley Capital International (MSCI) world equity market index, the S&P 500, the Commerzbank index of German equity, and the Nikkei) were negative. In only one case (dollar/yen on the MSCI World Index), beta was significantly positive with a value of 0.17. To determine whether the performance of trading rules can be explained by a given model for the data-generating process, Brock, Lakonishok, and LeBaron's bootstrap procedures were used with three null models (a random walk, ARMA, and ARMA-GARCH (1,1)). The best-performing ARMA model could explain only about 11% of the net returns to the dollar/mark rate yielded by 10 representative trading rules.

Ready (2002) compared the performance of technical trading rules developed by genetic programming to that of moving average rules examined by Brock, Lakonishok, and LeBaron (1992) for dividend-adjusted DJIA data. Brock, Lakonishok, and LeBaron's best trading rule (1/150 moving average without a band) for the 1963-1986 period generated substantially higher excess returns than the average of trading rules formed by genetic programming after transaction costs. For the 1957-1962 period, however, the moving average rule underperformed every one of genetic trading rules. Thus, it seemed unlikely that Brock, Lakonishok, and LeBaron's moving average rules would have been chosen by a hypothetical trader at the end of 1962. This led Ready to conclude that "the apparent success (after transaction costs) of the Brock, Lakonishok, and LeBaron (1992) moving average rules is a spurious result of data snooping" (p. 43). He further found that genetic trading rules performed poorly for each out-of-sample period, i.e., 1963-1986 and 1987-2000.

Similarly, Wang (2000) and Neely (2003) reported that genetically optimized trading rules failed to outperform the buy-and-hold strategy in both S&P 500 spot and futures markets. For example, Neely (2003) showed that genetic trading rules generated negative mean excess returns over the buy-and-hold strategy during the entire out-of-sample periods, 1936-1995. On the other hand, Neely and Weller (1999, 2001) documented the profitability of genetic trading rules in various foreign exchange markets, although trading profits appeared to gradually decline over time. Neely and Weller's (2001) finding indicated that technical trading profits for four major currencies were 1.7%-8.3% per year over the 1981-1992 period, but near zero or negative except for the yen over the 1993-1998 period. By testing intra-daily data in 1996, Neely and Weller (2003) also found that genetic trading rules realized break-even transaction costs of less than 0.02% for most major currencies, under realistic trading hours and transaction costs. Roberts (2003) documented that during the 1978-1998 period genetic trading rules generated a statistically significant mean net return (a daily mean profit of $1.07 per contract) in comparison to a buy-and-hold return (-$3.30) in a wheat futures market. For corn and soybeans futures markets, however, genetic trading rules produced both negative mean returns and negative ratios of profit to maximum drawdown. In sum, technical trading rules formulated by genetic programming appeared to be unprofitable in stock markets, particularly in recent periods. In contrast, genetic trading rules performed well in foreign exchange markets with their decreasing performance over time. In grain futures markets, the results were mixed.

The genetic programming approach may avoid data snooping problems caused by ex post selection of technical trading rules in the sense that the rules are chosen by using price data available before the beginning of the test period and thus all results are out-of-sample. However, the results of genetic programming studies may be confronted with a similar problem. That is, "it would be inappropriate to use a computer intensive genetic algorithm to uncover evidence of predictability *before* the algorithm or computer was available" (Cooper and Gulen 2003, p. 9). In addition, it is questionable whether trading rules formed by genetic programming have been used by real traders. A genetically trained trading rule is a "fit solution" rather than a "best solution" because it depends on the evolution of initially chosen random rules. Thus, numerous "fit" trading rules may be identified on the same in-sample data. For this reason, most researchers using the genetic programming technique have evaluated the "average" performance of 10 to 100 genetic trading rules. More importantly, trading rules formulated by a genetic program generally have a more complex structure than that of typical technical trading rules used by technical analysts. This implies that the rules identified by genetic programming may not approximate real technical trading rules applied in practice. Hence, studies applying genetic programming to sample periods ahead of its discovery violate the first two conditions suggested by Timmermann and Granger (2004), which indicate that forecasting experiments need to specify (1) the set of forecasting models available at any given point in time, including estimation methods; (2) the search technology used to select the best (or a combination of best) forecasting model(s).

Reality Check Studies

According to White (2000), "Data snooping occurs when a given set of data is used more than once for purposes of inference or model selection" (p. 1097). He argued that when such data re-use occurs, any satisfactory results obtained may simply be due to chance rather than to any merit inherent in the method yielding the results. Lo and MacKinlay (1990) also argued that "the more scrutiny a collection of data is subjected to, the more likely will interesting (spurious) patterns emerge" (p. 432). Indeed, in empirical studies of prediction, when there is little theoretical guidance regarding the proper selection of choice variables such as explanatory variables, assets, in-sample estimation periods, and others, researchers may select the choice variables "in either (1) an ad-hoc fashion, (2) to make the out-of-sample forecast work, or (3) by conditioning on the collective knowledge built up to that point (which may emanate from (1) and/or (2)), or some combination of the three" (Cooper and Gulen 2003, p. 3). Such data snooping practices inevitably overstate significance levels (e.g., t-statistic or $\bar{R}^2$) of conventional hypothesis tests (Lovell 1983; Denton 1985; Lo and MacKinlay 1990; Sullivan, Timmermann, and White 1999; Cooper and Gulen 2003).

In the literature on technical trading strategies, a fairly blatant form of data snooping is an ex post and "in-sample" search for profitable trading rules. Jensen (1967) argued that "if we begin to test various mechanical trading rules on the data we can be virtually certain that if we try enough rules with enough variants we will eventually find one or more which would have yielded profits (even adjusted for any risk differentials) superior to a buy-and-hold policy. But, and this is the crucial question, does this mean the same trading rule will yield superior profits when actually put into practice?" (p. 81). More subtle forms of data snooping are suggested by Cooper and Gulen (2003). Specifically, a set of data in technical trading research can be repeatedly used to search for profitable "families" of trading systems, markets, in-sample estimation periods, out-of-sample periods, and trading model assumptions including performance criteria and transaction costs. As an example, a researcher may deliberately investigate a number of in-sample optimization periods (or methods) on the same data to select one that provides maximum profits. Even if a researcher selects only one in-sample period in an ad-hoc fashion, it is likely to be strongly affected by similar previous research. Moreover, if there are many researchers who choose one individual in-sample optimization method on the same data, they are collectively snooping the data. Collective data snooping is potentially the most dangerous because it is not easily recognized by each individual researcher (Denton 1985).

White (2000) developed a statistical procedure that, unlike the genetic programming approach, can assess the effects of data snooping in the traditional framework of pre-determined trading rules. The procedure, which is called the Bootstrap Reality Check methodology, tests a null hypothesis that the best trading rule performs no better than a benchmark strategy. In this approach, the best rule is searched by applying a performance measure to the full set of trading rules, and a desired p-value can be obtained from comparing the performance of the best trading rule to approximations to the asymptotic distribution of the performance measure. Thus, White's approach takes account of dependencies across trading rules tested.

Sullivan, Timmermann, and White (1999) applied White's Bootstrap Reality Check methodology to 100 years of the Dow Jones Industrial Average (DJIA), from 1897 through 1996. They used the sample period (1897-1986) studied by Brock, Lakonishok, and LeBaron (1992) for in-sample tests and an additional 10 years from 1987-1996 for out-of-sample tests. S&P 500 index futures from 1984 through 1996 were also used to test the performance of trading rules. For the full set of technical trading rules, Sullivan, Timmermann, and White considered about 8,000 trading rules drawn from 5 simple technical trading systems that consisted of filters, moving averages, support and resistance, channel breakouts, and on-balance volume averages. Two performance measures, the mean return and the Sharpe ratio, were employed. A benchmark for the mean return criterion was the "null" system, which means out of market. In the case of the Sharpe ratio criterion, a benchmark of a risk-free rate was used, implying that technical trading rules earn the risk-free rate on days when a neutral signal is generated. Transaction costs were not incorporated directly.

The results for the mean return criterion indicated that during the 1897-1996 period the best rule was a 5-day moving average that produced an annual mean return of 17.2% with a Bootstrap Reality Check p-value of zero, which ensures that the return was not the result of data snooping. Since the average return was obtained from 6,310 trades (63.1 per year), the break-even transaction cost level was 0.27% per trade. The universe of 26 trading rules used by Brock, Lakonishok, and LeBaron (1992) was also examined. Among the trading rules, the best rule was a 50-day variable moving average rule with a 1% band, generating an annualized return of 9.4% with the Bootstrap Reality Check p-value of zero. Thus, the results of Brock, Lakonishok, and LeBaron (1992) were robust to data snooping biases.[20] These returns were compared with the average annual return of 4.3% on the buy-and-hold strategy during the same sample period. Similar results were obtained for the Sharpe ratio criterion. Over the full 100-year period, the buy-and-hold strategy generated a Sharpe ratio of 0.034, while Sharpe ratios for the best rules in Brock, Lakonishok, and LeBaron's universe and the full universe were 0.39 and 0.82, respectively. Although the Bootstrap Reality Check p-values were all zero for both cases, the best rules in Brock, Lakonishok, and LeBaron's study appeared to have insignificant p-values in several subperiods. Out-of-sample results were relatively disappointing. Over the 10-year (1987-1996) sample on the DJIA, the 5-day moving average rule selected as the best rule from the full universe over the 1897-1986 period yielded a mean return of 2.8% per year with a nominal p-value[21] of 0.32, indicating that the best rule did not continue to generate valuable economic signals in the subsequent period. For the S&P 500 futures index over the period 1984-1996, the best rule generated a mean return of 9.4% per year with a nominal p-value of 0.04. At first glance, thus, the rule seemed to produce a statistically significant return. However, the p-value adjusted for data snooping was 0.90, suggesting that the return was a result of data snooping. Sullivan, Timmermann, and White construed that the poor out-of-sample performance relative to the significant in-sample performance of technical trading rules might be related to the

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[20] This result contrasts sharply with the result of Ready (2002), who argued that Brock, Lakonishok, and LeBaron's results were spurious because of the data snooping problem.

[21] The nominal *p*-value was obtained from applying the Bootstrap Reality Check methodology only to the best rule, thereby ignoring the effect of data snooping.

recent improvement of the market efficiency due to the cheaper computing power, lower transaction costs, and increased liquidity in the stock market.

Table 6 presents summaries of the Reality Check studies. Sullivan, Timmermann, and White (2003) expanded the universe of trading rules by combining technical trading rules and calendar frequency trading rules[22] tested in their previous works (Sullivan, Timmermann, and White 1999, 2001). The augmented universe of trading rules was comprised of 17,298 trading rules. The results indicated that for the full sample period (1897-1998), the best of the augmented universe of trading rules, which was a 2-day-on-balance volume strategy, generated mean return of 17.1% on DJIA data with a data snooping adjusted p-value of zero and outperformed a buy-and-hold strategy (a mean return of 4.8%). For a recent period (1987-1996), the best rule was a week-of-the-month strategy with a mean return of 17.3% being slightly higher than a buy-and-hold return (13.6%). However, the return was not statistically significant with a data snooping adjusted p-value of 0.98. Similar results were found for the S&P 500 futures data. The best rule (a mean return of 10.7%) outperformed the benchmark (a mean return of 8.0%) during the 1984-1996 period, but a data snooping adjusted p-value was 0.99. Hence, they argued that it might be premature to conclude that both technical trading rules and calendar rules outperformed the benchmark in the stock market.

Qi and Wu (2002) applied White's Bootstrap Reality Check methodology to seven foreign exchange rates during the 1973-1998 period. They created the full set of rules with four trading systems (filters, moving averages, support and resistance, and channel breakouts) among five technical trading systems employed in Sullivan, Timmermann, and White (1999). Results indicated that the best trading rules, which were mostly moving average rules and channel breakout rules, produced positive mean excess returns over the buy-and-hold benchmark across all currencies and had significant data snooping adjusted p-values for the Canadian dollar, the Italian lira, the French franc, the British pound, and the Japanese yen. The mean excess returns were economically substantial (7.2% to 12.2%) for all the five currencies except for the Canadian dollar (3.6%), even after adjustment for transaction costs of 0.04% per one-way transaction. In addition, the excess returns could not be explained by systematic risk. Similar results were found for the Sharp ratio criterion, and the overall results appeared robust to incorporation transaction costs into the general trading model, changes in a vehicle currency, and changes in the smoothing parameter in the stationary bootstrap procedure. Hence, Qi and Wu concluded that certain technical trading rules were genuinely profitable in foreign exchange markets during the sample period.

By using White's Bootstrap Reality Check methodology, Sullivan, Timmermann, and White (1999, 2003) corroborated academics' belief regarding technical trading rules in their out-of-sample tests. However, several problems are found in their work. First, the universe of trading rules considered by Sullivan, Timmermann, and White (1999, 2003) may not represent the true universe of trading rules. For example, their first study assumed that rules from five simple technical trading systems represented the full set of technical trading rules. However, there may be numerous different technical trading systems such as various combination systems

[22] These calendar frequency trading rules are based on calendar effects documented in finance studies. Several famous calendar effects are the Monday effect, the holiday effect, the January effect, and the turn-of-the-month effect. See Schwert (2003) for further details.

that were not included in their full set of technical trading rules. If a set of trading rules tested is a subset of an even larger universe of rules, White's Bootstrap Reality Check methodology delivers a p-value biased toward zero under the assumption that the included rules in the "universe" performed quite well during the historical sample period. This can be illustrated by comparing the results of Sullivan, Timmermann, and White's studies. When only technical trading rules were tested on DJIA data over the 1987-1996 period, the best rule (a 200-day channel rule with 0.150 width and a 50-day holding period) generated an annual mean return of 14.41% with a p-value of 0.341. However, the best (a week-of-the-month rule) of the augmented universe of trading rules yielded an annual mean return of 17.27% with a p-value of 0.98 for the same data. Obviously, the former has a downward biased p-value. Second, transaction costs were not directly incorporated into the trading model. Transaction costs may have a significant effect on selection of the optimal trading rules. If Sullivan, Timmermann, and White considered mean *net* return as a performance measure, their best trading rules for the full in-sample period might be changed because incorporating transaction costs into a performance measure tends to penalize trading rules that generate more frequent transactions. In fact, Qi and Wu (2002) found that when they changed a performance measure from mean returns to mean net returns, the best trading rules selected were rules that generated less frequent trading signals than in case of the mean return criterion. Third, the data snooping effects of the best trading rule measured in terms of the Bootstrap Reality Check p-value in a sample period cannot be assessed in a different sample period (e.g., an out-of-sample period), because the best trading rule usually differs according to sample periods considered.

A final problem arises from White's (2000) procedure itself. In the testing procedure for superior predictive ability (SPA) such as White's procedure, the null hypothesis typically consists of multiple inequalities, which lead to a composite null hypothesis. One of the complications of testing a composite hypothesis is that the asymptotic distribution of the test statistic is not unique under the null hypothesis. The typical solution for the ambiguity in the null distribution is to apply the least favorable configuration (LFC), which is known as the points least favorable to the alternative hypothesis. This is exactly what White (2000) has done. However, Hansen (2003) showed that such a LFC-based test has some limitations because it does not ordinarily meet an "asymptotic similar condition" which is necessary for a test to be unbiased, and as a result it may be sensitive to the inclusion of poor forecasting models. In fact, the simulation and empirical results in Hansen (2003, 2004) indicated that the inclusion of a few poor-performing models severely reduces rejection probabilities of White's Reality Check test under the null, causing the test to be less powerful under the alternative. In research on technical trading systems, researchers generally search over a large number of parameter values in each trading system tested, because there is no theoretical guidance with respect to the proper selection of parameters. Thus, poor-performing trading rules are inevitably included in the analysis, and testing these trading rules with the Reality Check procedure may produce biased results.[23] Despite these limitations, Reality Check studies can be regarded as a substantial improvement over previous technical trading studies in that they attempted to explicitly quantify data snooping biases regarding the selection of technical trading rules.

[23] See Hansen (2003, 2004) for detailed discussion.

Chart Pattern Studies

Chart pattern studies test the profitability or forecasting ability of visual chart patterns widely used by technical analysts. Well-known chart patterns, whose names are usually derived from their shapes in bar charts, are gaps, spikes, flags, pennants, wedges, saucers, triangles, head-and-shoulders, and various tops and bottoms (see e.g. Schwager (1996) for detailed charting discussion). Previously, Levy (1971) documented the profitability of 32 five-point chart formations for NYSE securities. He found that none of the 32 patterns for any holding period generated profits greater than average purchase or short-sale opportunities. However, a more rigorous study regarding chart patterns was provided by Chang and Osler (1999).[24]

Chang and Osler evaluated the performance of the head-and-shoulders pattern using daily spot rates for 6 currencies (mark, yen, pound, franc, Swiss franc, and Canadian dollar) during the entire floating rate period, 1973-1994. The head-and-shoulders pattern can be described as a sequence of three peaks with the highest in the middle. The center peak is referred to as 'head', the left and right peaks around the head as 'shoulders', and the straight line connecting the troughs separating the head from right and left shoulders as 'the neckline'. The pattern is considered 'confirmed' when the price path penetrates the neckline after forming the right shoulder. Head-and-shoulders can occur both at peaks and at troughs, where they are called 'tops' and 'bottoms', respectively. After developing the head-and-shoulders identification and profit-taking algorithm, Chang and Osler established a strategy for entering and exiting positions based on such recognition. The entry position is taken when a current price breaks the neckline, while the timing of exit can be determined arbitrarily. They set up two kinds of exit rules: an endogenous rule and an exogenous rule. The endogenous rule includes both stop-loss and bounce. The stop-loss is triggered at 1% of the entry price to limit losses whenever price moves in the opposite direction to that expected by the head-and-shoulders. The bounce possibility is captured by the following strategy: if the down-trend of prices following a confirmed head-and-shoulders top turns up-trend before falling by at least 25% of the vertical distance from the head to the neckline, then investors hold their current positions until either prices cross back over the neckline by at least 1% (stop-loss) or a second trough (of any size) is reached in the zigzag. The exogenous rule is to close an open position after an exogenously specified number of days from the entry point. One to 60 (1, 3, 5, 10, 20, 30, and 60) days were considered.

For the endogenous exit rule, head-and-shoulders rules generated statistically significant returns of about 13% and 19% per year for the mark and yen, respectively, but not for the other exchange rates. Returns from the exogenous exit rule appeared to be insignificant in most cases. The trading profits from the endogenous exit rules were substantially higher than either the annual buy-and-hold returns of 2.5% for the mark and 4.4% for the yen or annual average stock yield of 6.8% measured on the S&P 500 index. The head-and-shoulders returns for the mark and yen were also significantly greater than those derived from 10,000 simulated random walk data series obtained from a bootstrap method and were substantial even after adjusting for transaction costs of 0.05% per round-trip, interest differential, and risk. For example, the Sharpe ratios for the mark and yen were1.00 and 1.47, respectively, while the Sharpe ratio for the S&P 500 was 0.32. Moreover, it turned out that the returns were not compensation for bearing systematic risk,

[24] In fact, Brock, Lakonishok, and LeBaron's trading range breakout rules (support and resistance levels) can be regarded as chart patterns.

since none of the estimated betas were statistically significantly different from zero with the largest beta being 0.03. Profits for the mark and yen were also robust to changes in the parameters of the head-and-shoulders recognition algorithm, changes in the sample period, and the assumption that exchange rates follow a GARCH (1,1) process rather than the random walk model. Over the sample period, a portfolio that consisted of all six currencies earned total returns of 69.9%, which were significantly higher than returns produced in the simulated data.

Chang and Osler further investigated the performance of moving average rules and momentum rules and compared the results with the observed performance of the head-and-shoulders rule. Returns from the simple technical trading systems appeared statistically significant for all six currencies and the simpler rules easily outperformed the head-and-shoulders rules in terms of total profits and the Sharpe ratios. To evaluate the incremental contribution of the head-and-shoulders rule when combined with each of simpler rules, combination rules of both strategies were simulated on the mark and yen. Results indicated that each combination rule generated slightly higher returns than the simple rule alone, but significantly increased risk (daily variation of returns). Hence, Chang and Osler concluded that, although the head-and-shoulders patterns had some predictive power for the mark and yen during the period of floating exchange rates, the use of the head-and-shoulders rule did not seem to be rational, because they were easily dominated by simple moving average rules and momentum rules and increased risk without adding significant profits when used in combination with the simpler rules.

Table 7 summarizes other chart pattern studies. Lo, Mamaysky, and Wang (2000) examined more chart patterns. They evaluated the usefulness of 10 chart patterns, which are the head-and-shoulders (HS) and inverse head-and-shoulders (IHS), broadening tops (BTOP) and bottoms (BBOT), triangle tops (TTOP) and bottoms (TBOT), rectangle tops (RTOP) and bottoms (RBOT), and double tops (DTOP) and bottoms (DBOT). To see whether these technical patterns are informative, goodness-of-fit and Kolmogorov-Smirnov tests were applied to the daily data of individual NYSE/AMEX stocks and Nasdaq stocks during the 1962-1996 period. The goodness-of-fit test compares the quantiles of returns conditioned on technical patterns with those of unconditional returns. If the technical patterns provide no incremental information, both conditional and unconditional returns should be similar. The Kolmogorov-Smirnov statistic was designed to test the null hypothesis that both conditional and unconditional empirical cumulative distribution functions of returns are identical. In addition, to evaluate the role of volume, Lo, Mamaysky, and Wang constructed three return distributions conditioned on (1) technical patterns; (2) technical patterns and increasing volume; and (3) technical patterns and decreasing volume.

The results of the goodness-of-fitness test indicated that the NYSE/AMEX stocks had significantly different relative frequencies on the conditional returns from those on the unconditional returns for all but 3 patterns, which were BBOT, TTOP, and DBOT. On the other hand, Nasdaq stocks showed overwhelming significance for all the 10 patterns. The results of the Kolmogorov-Smirnov test showed that, for the NYSE/AMEX stocks, 5 of the 10 patterns (HS, BBOT, RTOP, RBOT, and DTOP) rejected the null hypothesis, implying that the conditional distributions of returns for the 5 patterns were significantly different from the unconditional distributions of returns. For the Nasdaq stocks, in contrast, all the patterns were statistically significant at the 5% level. However, volume trends appeared to provide little incremental information for both stock markets with a few exceptions. The difference between the conditional distributions of increasing and decreasing volume trends was statistically insignificant for most patterns in both NYSE/AMEX and Nasdaq markets. Hence, Lo, Mamaysky, and Wang concluded that technical patterns did provide some incremental information, especially, for the NASDAQ stocks. They argued that "Although this does not necessarily imply that technical analysis can be used to generate 'excess' trading profits, it does raise the possibility that technical analysis can add value to the investment process" (p. 1753). In terms of trading profits, Dawson and Steeley (2003) confirmed the argument by applying the same technical patterns as in Lo, Mamaysky, and Wang (2000) to UK data. Although they found return distributions conditioned on technical patterns were significantly different from the unconditional distributions, an average market adjusted return turned out to be negative across all technical patterns and sample periods they considered.

Caginalp and Laurent (1998) reported that candlestick reversal patterns generated substantial profits in comparison to an average gain for the same holding period. For the S&P 500 stocks over the 1992-1996 period, down-to-up reversal patterns produced an average return of 0.9% during a two-day holding period (annually 309% of the initial investment). The profit per trade ranged from 0.56%-0.76% even after adjustment for commissions and bid-ask spreads on a $100,000 trade, so that the initial investment was compounded into 202%-259% annually. Leigh, Paz, and Purvis (2002) and Leigh et al. (2002) also noted that bull flag patterns for the NYSE Composite Index generated positive excess returns over a buy-and-hold strategy before transaction costs. However, Curcio et al. (1997), Guillaume (2000), and Lucke (2003) all showed limited evidence of the profitability of technical patterns in foreign exchange markets, with trading profits from the patterns declining over time (Guillaume 2000). In general, the results of chart pattern studies varied depending on patterns, markets, and sample periods tested, but suggested that some chart patterns might have been profitable in stock markets and foreign exchange markets. Nevertheless, all studies in this category, except for Leigh, Paz, and Purvis (2002), neither conducted parameter optimization and out-of-sample tests, nor paid much attention to data snooping problems.

Nonlinear Studies

Nonlinear studies attempted to directly measure the profitability of a trading rule derived from a nonlinear model, such as the feedforward networks or the nearest neighbors regressions, or evaluate the nonlinear predictability of asset returns by incorporating past trading signals from simple technical trading rules (e.g., moving average rules) or lagged returns into a nonlinear model. A single layer feedforward network regression model with *d* hidden layer units and with lagged returns is typically given by

$$y_t = F\left(a_0 + \sum_{j=1}^{d} b_j G\left(a_j + \sum_{i=1}^{p} g_{ij} r_{t-i}\right) + e_t\right), \quad e_t \sim ID(0, s_t^2), \tag{6}$$

where y_t is an indicator variable which takes either a value of 1 (for a long position) or –1 (for a short position) and $r_{t-i} = \log(P_{t-i} / P_{t-i-1})$ is the return at time $t-i$. Sometimes, the lagged returns are replaced with trading signals generated by a simple technical trading rule such as a moving average rule. Each hidden layer unit receives the weighted sum of all inputs and a bias term and generates an output signal through the hidden transfer function (G), where g_{ij} is the weight of its connection from the ith input unit to the jth hidden layer unit. In the similar manner, the output unit receives the weighted sum of the output signals of the hidden layer and generates a signal through the output transfer function (F), where b_j is the weight of the connection from the jth hidden layer unit. For example, in Gençay (1998a), the number of hidden layer units was selected to be {1, 2, …, 15} and p was set to 9. Gençay argued that "under general regularity conditions, a sufficiently complex single hidden layer feedforward network can approximate any member of a class of functions to any desired degree of accuracy where the complexity of a single hidden layer feedforward network is measured by the number of hidden units in the hidden layer" (p. 252).

Gençay (1998a) tested the profitability of simple technical trading rules based on a feedforward network using DJIA data for 1963-1988. Across 6 subsample periods, the technical trading rules generated annual net returns of 7%-35% after transaction costs and easily dominated a buy-and-hold strategy. The results for the Sharpe ratio were similar. Hence, the technical trading rule outperformed the buy-and-hold strategy after transaction costs and risk were taken into account. In addition, correct sign predictions for the recommended positions ranged 57% to 61%.

Other nonlinear studies are summarized in Table 8. Gençay (1998b, 1999) further investigated the nonlinear predictability of asset returns by incorporating past trading signals from simple technical trading rules, i.e., moving average rules, or lagged returns into a nonlinear model, either the feedforward network or the nearest neighbor regression. Out-of-sample results regarding correct sign predictions and the mean square prediction error (MSPE) indicated that, in general, both the feedforward network model and the nearest neighbor model yielded substantial forecast improvement and outperformed the random walk model or GARCH (1,1) model in both stock and foreign exchange markets. In particular, the nonlinear models based on past buy-sell signals of the simple moving average rules provided more accurate predictions than those based on past returns. Gençay and Stengos (1998) extended previous nonlinear studies by incorporating a 10-day volume average indicator into a feedforwad network model as an additional regressor. For the same DJIA data as used in Gençay (1998a), the nonlinear model produced an average of 12% forecast gain over the beanchmark (an OLS model with lagged returns as regressors) and provided much higher correct sign predictions (an average of 62%) than other linear and nonlinear models. Fernández-Rodríguez, González-Martel, and Sosvilla-Rivero (2000) applied the feedback network regression to the Madrid Stock index, finding that their technical trading rule outperformed the buy-and-hold strategy before transaction costs. Sosvilla-Rivero, Andrada-Félix, and Fernández-Rodríguez (2002) also showed that a trading rule based on the nearest neighbor regression earned net returns of 35% and 28% for the mark and yen, respectively, during the 1982-1996 period, and substantially outperformed buy-and-hold strategies. They further showed that when eliminating days of US intervention, net returns from the trading strategy substantially declined to -10% and -28% for the mark and yen, respectively. Fernández-Rodríguez, Sosvilla-Rivero, and Andrada-Félix (2003) found that simple trading rules based on the nearest neighbors model were superior to moving average rules in European exchange markets for 1978-1994. Their nonlinear trading rules generated statistically significant annual net returns of 1.5%-20.1% for the Danish krona, French franc, Dutch guilder, and Italian lira. In general, technical trading rules based on nonlinear models appeared to have either profitability or predictability in both stock and foreign exchange markets. However, nonlinear studies have a similar problem to that of genetic programming studies. That is, as suggested by Timmermann and Granger (2004), it may be improper to apply the nonlinear approach that was not available until recent years to reveal the profitability of technical trading rules. Furthermore, these studies typically ignored statistical tests for trading profits, and might be subject to data snooping problems because they incorporated trading signals from only one or two popular technical trading rules into the models.

Other Studies

Other studies are ones that do not belong to any categories reviewed so far. In general, these studies are similar to the early studies in that they did not conduct trading rule optimization and out-of-sample verification and address data snooping problems, although several studies (Sweeney 1988; Farrell and Olszewski 1993; Irwin et al. 1997) performed out-of-sample tests.

Neely (1997) tested the profitability of filter rules and moving average rules on four major exchange rates (the mark, yen, pound sterling, and Swiss franc) over the 1974-1997 period. Filter rules included six filters from 0.5% to 3% with window lengths of 5 business days to identify local extremes and moving average rules consisted of four dual moving averages (1/10, 1/50, 5/10, 5/50). The results indicated that trading rules yielded positive net returns in 38 of the 40 cases after deducting transaction costs of 0.05% per round-trip. Specifically, for the mark, 9 of the 10 trading rules generated positive net returns with an annual mean net return of 4.4%. These trading profits did not seem to be compensation for bearing risk. In terms of Sharpe ratios, every moving average rule (average of 0.6) and two filter rules outperformed a buy-and-hold strategy (0.3) in the S&P 500 Index over the same sample period. The CAPM betas estimated from the 10 trading rules also generally indicated zero or negative correlation with the S&P 500 monthly returns. The results for other exchange rates were similar. Hence, the trading rules, especially moving average rules, appeared to be profitable beyond transaction costs and risk. However, Neely argued that the apparent success of the technical trading rules might not necessarily implicate market inefficiency because of problems in testing procedure, such as difficulties in getting actual prices and interest rates, the absence of a proper measure of risk, and data snooping. In particular, he emphasized data snooping problems in studies of technical analysis by noting that "the rules tested here are certainly subject to a data-mining bias, since many of them had been shown to be profitable on these exchange rates over at least some of the subsample" (p. 32).

Table 9 summarizes other studies in this category. As an exceptional case among the studies, Neftci's (1991) work is close to a theoretical study. Using the notion of Markov times, he demonstrated that the moving average rule was one of the few mathematically well-defined technical analysis rules. Markov times are defined as random time periods, whose value can be determined by looking at the current information set (p. 553). Therefore, Markov times do not rely on future information. If a trading rule generates a sequence of trading signals that fail to be Markov times, it would be using future information to emit such signals. However, various patterns or trend crossings in technical analysis, such as "head-and-shoulders" and "triangles," did not appear to generate Markov times. To verify whether 150-day moving average rule has predictive value, Neftci incorporated trading signals of the moving average rule into a dummy variable in an autoregression equation. For the Dow-Jones Industrials, F-test results on the variable were insignificant over the 1795-1910 period but highly significant over the 1911-1976 period. Hence, the moving average rule seemed to have some predictive power beyond the own lags of the Dow-Jones Industrials.

Pruitt and White (1988) and Pruitt, Tse, and White (1992) documented that a combination system consisting of cumulative volume, relative strength, and moving average (CRISMA) was profitable in stock markets. For example, Pruitt, Tse, and White (1992) obtained annual excess returns of 1.0%-5.2% after transaction costs of 2% over the 1986-1990 period and found that the CRISMA system outperformed the buy-and-hold or market index strategy. Sweeney (1988) and Corrado and Lee (1992) also found that filter-based rules outperformed buy-and-hold strategies after transaction costs in stock markets. Schulmeister (1988) and Dewachter (2001) reported the profitability of various technical trading rules in foreign exchange markets, but Marsh (2000) showed that technical trading profits in foreign exchange markets decreased in the recent period. Irwin et al. (1997) compared the performance of the channel trading system to ARIMA models in soybean-related futures markets. During their out-of-sample period (1984-1988), the channel system generated statistically significant mean returns ranging 5.1%-26.6% across the markets and beat the ARIMA models in every market. Overall, studies in this category indicated that technical trading rules performed quite well in stock markets, foreign exchange markets, and grain futures markets. As noted above, however, these studies typically omitted trading rule optimization and out-of-sample verification and did not address data snooping problems.

Summary of Modern Studies

Modern studies greatly improved analytic techniques relative to those of early studies, with more advanced theories and statistical methods spurred on by rapid growth of computing power. Modern studies were categorized into seven groups based on their testing procedures. “Standard” studies (Lukac, Brorsen, and Irwin 1988; Lukac and Brorsen 1990; and others) comprehensively tested the profitability of technical trading rules using parameter optimization, out-of-sample verification, and statistical tests for trading profits. In addition, transaction costs and risk were incorporated into the general trading model. Standard studies, in general, found that technical trading profits were available in speculative markets. Taylor (2000) obtained a break-even one-way transaction cost of 1.07% for the DJIA data during the 1968-1988 period using an optimized moving average rule. Szakmary and Mathur (1997) showed that moving average rules produced annual net returns of 3.5%-5.4% in major foreign exchange markets for 1978-1991, although the profits of moving average rules in foreign exchange markets tend to dissipate over time (Olsen 2004). Lukac, Brorsen, and Irwin (1988) also found that four technical trading systems, the dual moving average crossover, close channel, MII price channel, and directional parabolic, yielded statistically significant portfolio annual net returns ranging from 3.8%-5.6% in 12 futures markets during the 1978-1984 period. Nevertheless, since these studies did not explicitly address data snooping problems, there is a possibility that the successful results were caused by chance.

“Model-based bootstrap” studies (Brock, Lakonishok, and LeBaron 1992; Levich and Thomas 1993; Bessembinder and Chan 1998; and others) conducted statistical tests for trading returns using model-based bootstrap approaches pioneered by Brock, Lakonishok, and LeBaron (1992). In these studies, popular technical trading rules, such as moving average rules and trading range breakout rules, were tested in an effort to reduce data snooping problems. The results of the model-based bootstrap studies differed across markets and sample periods tested. In general, technical trading strategies were profitable in several emerging (stock) markets and foreign exchange markets, while they were unprofitable in developed stock markets (e.g., US markets). Ratner and Leal (1999) found that moving average rules generated statistically significant annual net returns of 18.2%-32.1% in stock markets of Mexico, Taiwan, Thailand, and the Philippines during the 1982-1995 period. LeBaron (1999) also showed that a 150 moving average rule for the mark and yen generated Sharpe ratios of 0.60-0.98 after a transaction cost of 0.1% per round-trip over the 1979-1992 period, which were much greater than those (0.3-0.4) for buy-and-hold strategies on aggregate US stock portfolios. However, Bessembinder and Chan (1998) noted that profits from Brock, Lakonishok, and LeBaron's (1992) trading rules for the DJIA index declined substantially over time. In particular, an average break-even one-way transaction cost across the trading rules in a recent period (1976-1991) was 0.22%, which was compared to estimated one-way transaction costs of 0.24%-0.26%. As pointed out by Sullivan, Timmermann, and White (1999), on the other hand, popular trading rules may have survivorship bias, which implies that they may have been profitable over a long historical period by chance. Moreover, model-based bootstrap studies often omitted trading rule optimization and out-of-sample verification.

"Genetic programming" studies (Neely, Weller, and Dittmar 1997; Allen and Karjalainen 1999; Ready 2002; and others) attempted to avoid data snooping problems by testing ex ante trading rules optimized by genetic programming techniques. In these studies, out-of-sample verification for the optimal trading rules was conducted together with statistical tests, and transaction costs and risk were incorporated into the testing procedure. Genetic programming studies generally indicated that technical trading rules formulated by genetic programming might be successful in foreign exchange markets but not in stock markets. For example, Allen and Karjalainen (1999), Ready (2002), and Neely (2003) all documented that over a long time period, genetic trading rules underperformed buy-and-hold strategies for the S&P 500 index or the DJIA index. In contrast, Neely and Weller (2001) obtained annual net profits of 1.7%-8.3% for four major currencies over the 1981-1992 period, although profits decreased to around zero or were negative except for the yen over the 1993-1998 period. The results for futures markets varied depending on markets tested. Roberts (2003) obtained a statistically significant daily mean net profit of $1.07 per contract in the wheat futures market for 1978-1998, which exceeded a buy-and-hold return of -$3.30 per contract, but found negative mean net returns for corn and soybean futures markets. The genetic programming technique may become an alternative approach to test technical trading rules because it provides a sophisticated search procedure. However, it was not applied to technical analysis until the mid-1990s, and moreover, the majority of optimal trading rules identified by a genetic program appeared to have more complex structures than that of typical technical trading rules. Hence, there has been strong doubt as to whether actual traders could have used these trading rules. Cooper and Gulen (2003) and Timmermann and Granger (2004) suggested that the genetic programming method must not be applied to sample periods before its discovery.

"Reality Check" studies (Sullivan, Timmermann, and White 1999, 2003; Qi and Wu 2002) use White's Bootstrap Reality Check methodology to directly quantify the effects of data snooping. White's methodology delivers a data snooping adjusted p-value by testing the performance of the best rule in the context of the full universe of trading rules. Thus, the approach accounts for dependencies across trading rules tested. Reality Check studies by Sullivan, Timmermann, and White (1999, 2003) provide some evidence that technical trading rules might be profitable in the stock market until the mid-1980s but not thereafter. For example, Sullivan, Timmermann, and White (1999) obtained an annual mean return of 17.2% (a break-even transaction cost of 0.27% per trade) from the best rule for the DJIA index over the 1897-1996 period, with a data-snooping adjusted p-value of zero. However, in an out-of-sample period (1987-1996), the best rule optimized over the 1897-1986 period yielded an annual mean return of only 2.8%, with a nominal p-value of 0.32. For the foreign exchange market, on the other hand, Qi and Wu (2002) obtained economically and statistically significant technical trading profits over the 1973-1998 period. They found mean excess returns of 7.2%-12.2% against the buy-and-hold strategy for major currencies except for the Canadian dollar (3.63%) after adjustment for transaction costs and risk. Despite the fact that Reality Check studies use a statistical procedure that can account for data snooping effects, they also have some problems. For example, there is difficulty in constructing the full universe of technical trading rules. Furthermore, if a set of trading rules tested is selected from an even larger universe of rules, a p-value calculated by the methodology could be biased toward zero under the assumption that the included rules in the "universe" performed quite well during the sample period.

"Chart patterns" studies (Chang and Osler 1999; Lo, Mamaysky, and Wang 2000; and others) developed and simulated algorithms that can recognize visible chart patterns used by technical analysts. In general, the results of chart pattern studies varied depending on patterns, markets, and sample periods tested, but suggested that some chart patterns might have been profitable in stock markets and foreign exchange markets. For example, Chang and Osler (1999) showed that the head-and-shoulders pattern generated statistically significant returns of about 13% and 19% per year for the mark and yen, respectively, for 1973-1994. These returns appeared to be substantially higher than either buy-and-hold returns or average stock yields on the S&P 500 index, and were still retained after taking account of transaction costs, interest differential, and risk. Similarly, Caginalp and Laurent (1998) found that for the S&P 500 stocks, down-to-up candlestick reversal patterns earned mean net returns of 0.56%-0.76% during a two-day holding period (annually 202%-259% of the initial investment) after transaction costs over the 1992-1996 period. Nevertheless, most studies in this category neither conducted parameter optimization and out-of-sample tests, nor paid much attention to data snooping problems.

"Nonlinear" studies (Gençay 1998a; Gençay and Stengos 1998; Fernández-Rodríguez, González-Martel, and Sosvilla-Rivero 2000; and others) investigated either the informational usefulness or the profitability of technical trading rules based on nonlinear methods, such as the nearest neighbor or the feedforward network regressions. Nonlinear studies showed that technical trading rules based on nonlinear models possessed profitability or predictability in both stock and foreign exchange markets. Gençay (1998a) found that simple technical trading rules based on a feedforward network for the DJIA index generated annual net returns of 7%-35% across 6 subsample periods over the 1963-1988 period and easily dominated a buy-and-hold strategy. Sosvilla-Rivero, Andrada-Félix, and Fernández-Rodríguez (2002) also showed that a trading rule based on the nearest neighbor regression earned net returns of 35% and 28% for the mark and yen, respectively, during the 1982-1996 period, and substantially outperformed buy-and hold strategies. However, nonlinear studies have a similar problem to that of genetic programming studies. That is, it may be improper to apply the nonlinear approach that was not available until recent years to reveal the profitability of technical trading rules. Furthermore, these studies typically ignored statistical tests for trading profits, and might be subject to data snooping problems because they incorporated trading signals from only one or two popular technical trading rules into the models.

"Other studies" include all studies that do not belong to any categories described in the above. Testing procedures of these studies are similar to those of the early studies, in that they did not conduct trading rule optimization and out-of-sample verification, with a few exceptions. Studies in this category suggested that technical trading rules performed quite well in stock markets, foreign exchange markets, and grain futures markets. Neely (1997) tested filter rules and moving average rules on four major exchange rates over the 1974-1997 period and obtained positive net returns in 38 of the 40 cases after adjusting for transaction costs. Pruitt, Tse, and White (1992) found that the CRISMA (combination of cumulative volume, relative strength, and moving average) system earned annual mean excess returns of 1.0%-5.2% after transaction costs in stock markets for 1986-1990 and outperformed the B&H or market index strategy. For soybean-related futures markets, Irwin et al. (1997) reported that channel rules generated statistically significant mean returns ranging 5.1%-26.6% over the 1984-1988 period and beat the ARIMA models in every market they tested. However, it is highly likely that these successful findings were attainable due to data snooping.

Table 10 summarizes the results of modern studies. As shown in the table, the number of studies that identified profitable technical trading strategies is far greater than the number of studies that found negative results. Among a total of 92 modern studies, 58 studies found profitability (or predictability) in technical trading strategies, while 24 studies reported negative results. The rest (10 studies) indicated mixed results. In every market, the number of profitable studies is twice that of unprofitable studies. However, modern studies also indicated that technical trading strategies had been able to yield economic profits in US stock markets until the late 1980s, but not thereafter (Bessembinder and Chan 1998; Sullivan, Timmermann, and White 1999; Ready 2002). Several studies found economic profits in emerging (stock) markets, regardless of sample periods considered (Bessembinder and Chan 1995; Ito 1999; Ratner and Leal 1999). For foreign exchange markets, it seems evident that technical trading strategies have made economic profits over the last few decades, although some studies suggested that technical trading profits have declined or disappeared in recent years (Marsh 2000; Neely and Weller 2001; Olson 2004). For futures markets, technical trading strategies appeared to be profitable between the mid-1970s and the mid-1980s. No study has yet comprehensively documented the profitability of technical trading strategies in futures markets after that period.

Summary and Conclusion

This report reviewed survey studies, theories and empirical work regarding technical trading strategies. Most survey studies indicate that technical analysis has been widely used by market participants in futures markets and foreign exchange markets, and that at least 30% to

40% of practitioners regard technical analysis as an important factor in determining price movement at shorter time horizons up to 6 months.

In the theoretical literature, the conventional efficient markets models, such as the martingale and random walk models, rule out the existence of profitable technical trading rules because both models assume that current prices fully reflect all available information. On the other hand, several other models, such as noisy rational expectations models, feedback models, disequilibrium models, herding models, agent-based models, and chaos theory, suggest that technical trading strategies may be profitable because they presume that price adjusts sluggishly to new information due to noise, market power, traders' irrational behavior, and chaos. In these models, thus, there exist profitable trading opportunities that are not being exploited. Such sharp disagreement in theoretical models makes empirical evidence a key consideration in determining the profitability of technical trading strategies.

More than 130 empirical studies have examined the profitability of technical trading rules over the last four decades. In this report, empirical studies were categorized into two groups, "early" studies and "modern" studies depending on the characteristics of testing procedures. In general, the majority of early studies examined one or two technical trading systems, and deducted transaction costs to compute net returns of trading rules. In these studies, however, risk was not adequately handled, statistical tests of trading profits and data snooping problems were often ignored, and out-of-sample tests along with parameter optimization were not conducted, with a few exceptions. The results of early studies varied from market to market. Overall, studies of stock markets found very limited evidence of the profitability of technical trading strategies, while studies of foreign exchange markets and futures markets frequently obtained sizable net profits. For example, Fama and Blume (1966) reported that for 30 individual securities of the Dow Jones Industrial Average (DJIA) over the 1956-1962 period, long signals of a 0.5% filter rule generated an average annual net return of 12.5% that was not much different from the buy-and-hold returns. In contrast, Sweeney (1986) found that for the majority of 10 major currencies small filter rules produced economically and statistically significant mean excess returns (3%-7%) over the buy-and-hold returns during the 1973-1980 period. Irwin and Uhrig (1984) also reported that several technical trading systems such as channel, moving average, and momentum oscillator systems generated substantial net returns in corn, cocoa, sugar, and soybean futures markets over the 1973-1981 period.

Modern studies improved upon the drawbacks of early studies and typically included some of the following features in their testing procedures: (1) the number of trading systems tested increased relative to early studies; (2) transaction costs and risk were incorporated (3) parameter (trading rule) optimization and the out-of-sample verification were conducted; and (4) statistical tests were performed with either conventional statistical tests or more sophisticated bootstrap methods, or both. In this report, modern studies were divided into seven groups based on their testing procedures: *i*) standard, *ii*) model-based bootstrap, *iii*) genetic programming, *iv*) Reality Check, *v*) chart patterns, *vi*) nonlinear, and *vii*) others. Modern studies indicated that technical trading strategies had been able to yield economic profits in US stock markets until the late 1980s, but not thereafter (Bessembinder and Chan 1998; Sullivan, Timmermann, and White 1999; Ready 2002). For example, Taylor (2000) obtained a break-even one-way transaction cost of 1.07% per transaction for the DJIA data over the 1968-1988 period using a

5/200-day moving average rule optimized over the 1897-1968 period,[25] while Sullivan, Timmermann, and White (1999) showed that the best rule (a 1/5-day moving average rule) optimized over the 1897-1986 period yielded a statistically insignificant annual mean return of only 2.8% for 1987-1996. Several studies found economic profits in emerging (stock) markets, regardless of the sample periods tested (Bessembinder and Chan 1995; Ito 1999; Ratner and Leal 1999). For foreign exchange markets, it seems evident that technical trading strategies had been profitable at least until the early 1990s, because many modern studies found net profits of around 5%-10% for major currencies (the mark, yen, pound, and Swiss franc) in their out-of-sample tests (Taylor 1992, 1994; Silber 1994; Szakmary and Mathur 1997; Olsen 2004). However, a few studies suggested that technical trading profits in foreign exchange markets have declined in recent years (Marsh 2000; Neely and Weller 2001; Olson 2004).[26] For example, Olson (2004) reported that risk-adjusted profits of moving average rules for an 18-currency portfolio declined from over 3% between the late 1970s and early 1980s to about zero percent in the late 1990s. For futures markets, technical trading strategies appeared to be profitable between the mid-1970s and the mid-1980s. For example, Lukac, Brorsen, and Irwin (1988) found that several technical trading systems, such as the dual moving average crossover, close channel, MII price channel, and directional parabolic systems, yielded statistically significant portfolio annual net returns ranging from 3.8%-5.6% in 12 futures markets during the 1978-1984 period. However, no study has yet comprehensively documented the profitability of technical trading strategies after that period.

Despite positive evidence about profitability and improved procedures for testing technical trading strategies, skepticism about technical trading profits remains widespread among academics. For example, in a recent and highly-regarded textbook on asset pricing, Cochrane (2001) argues that: “Despite decades of dredging the data, and the popularity of media reports that purport to explain where markets are going, trading rules that reliably survive transactions costs and do not implicitly expose the investor to risk have not yet been reliably demonstrated (p. 25).” As Cochrane points out, the skepticism seems to be based on data snooping problems and potentially insignificant economic profits after appropriate adjustment for transaction costs and risk. In this context, Timmermann and Granger (2004, p. 16) provide a detailed guide to the key issues that future studies of the profitability of technical trading systems must address:

1. The set of forecasting models available at any given point in time, including estimation methods.
2. The search technology used to select the best (or a combination of best) forecasting model(s).
3. The available ‘real time’ information set, including public versus private information and ideally the cost of acquiring such information.
4. An economic model for the risk premium reflecting economic agents’ trade-off between current and future payoffs.

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[25] Readers should carefully interpret this result. A break-even one-way transaction cost indicates gross return per trade. For instance, if the trading rule generates ten trades per year, the corresponding annual mean return would be 10.7%.

[26] One notable exception is the Japanese yen market in which the three studies found net profits even in recent periods.

5. The size of transaction costs and the available trading technologies and any restrictions on holdings of the asset in question.

The first two issues above focus squarely on the question of data snooping. In many previous studies, technical trading rules that produced significant returns were selected for investigation ex post. These profitable trading rules may have been selected because they were popular or widely used over time. However, there is no guarantee that the trading rules were chosen by actual investors at the beginning of the sample period. Similarly, studies using genetic algorithm or artificial neural networks often apply these relatively new techniques to the sample period before their discovery. Results of these studies are likely to be spurious because the search technologies were hardly available during the sample period. Therefore, the set of trading models including trading rules and other assumptions and the search technologies need to be specified.

Two possible approaches to handle data snooping problems in studies of technical trading strategies have been proposed. The first is to simply replicate previous results on a new set of data (e.g., Lovell 1983; Lakonishok and Smidt 1988; Lo and MacKinlay 1990; Schwert 2003; Sullivan, Timmermann, and White 2003). If another successful result is obtained from a new dataset by using the same procedure as used in an original study, we can be more confident the profitability (or predictability) of the original procedure. For a study to be replicated, however, the following three conditions should be satisfied: (1) the markets and trading systems tested in the original study should be comprehensive, in the sense that results can be considered broadly representative of the actual use of technical systems; (2) testing procedures must be carefully documented, so they can be "frozen" at the point in time the study was published, and (3) the original work should be published long enough ago that a follow-up study can have a sufficient sample size. Thus, if there is no sufficient new data or a lack of rigorous and comprehensive documentation about trading model assumptions and procedures, this approach may not be valid. Another approach is to apply White's (2000) Bootstrap Reality Check methodology, in which the effect of data snooping is directly quantified by testing the null hypothesis that the performance of the best rule in the full universe of technical trading rules is no better than the performance of a benchmark. This approach thus accounts for dependencies across all technical trading rules tested. However, a problem with White's bootstrap methodology is that it is difficult to construct the full universe of technical trading rules. Moreover, there still remain the effects of data snooping from other choice variables, such as markets, in-sample estimation periods, out-of-sample periods, and trading model assumptions including performance criteria and transaction costs, because White's procedure only captures data snooping biases caused by the selection of technical trading rules.

The third issue raised by Timmermann and Granger may not be a critical factor in technical trading studies because the information set used typically consists of prices and volume that are easily obtainable in real time, with low costs. The fourth and the fifth issues have the potential to be major factors. It is well known that risk is difficult to estimate because there is no generally accepted measure or model. Timmermann and Granger (2004) argue that "most models of the risk premium generate insufficient variation in economic risk-premia to explain existing asset pricing puzzles" (p. 18). In studies of technical analysis, the Sharpe ratio and the CAPM beta may be the most widely used risk measures. However, these measures have some well-known limitations. For example, the Sharpe ratio penalizes the variability of profitable returns exactly the same as the variability of losses, despite the fact that investors are more concerned about downside volatility in returns rather than total volatility (i.e., the standard deviation). This leads Schwager (1985) and Dacorogna et al. (2001) to propose different risk-adjusted performance measures that take into account drawbacks of the Sharpe ratio. These measures may be used as alternatives or in conjunction with the Sharpe ratio. The CAPM beta is also known to have the joint-hypothesis problem. Namely, when abnormal returns (positive intercept) are found, researchers can not differentiate whether they were possible because markets were truly inefficient or because the CAPM was a misspecified model. It is well-known that the CAPM and other multifactor asset pricing models such as the Fama-French three factor model are subject to "bad model" problems (Fama 1998). The CAPM failed to explain average returns on small stocks (Banz 1981), and the Fama-French three factor model does not seem to fully explain average returns on portfolios built on size and book-to-market equity (Fama and French 1993). Cochrane (2001, p. 465) suggests that some version of the consumption-based model, such as Constantinides and Duffie's (1996) model with uninsured idiosyncratic risks and Campbell and Cochrane's (1999) habit persistence model, may be an answer to the bad model problems in the stock market and even explain the predictability of returns in other markets (like bond and foreign currency markets).

The last issue is associated with market microstructure. Transaction costs generally consist of two components: (1) brokerage commissions and fees and (2) bid-ask spreads. Commissions and fees are readily observable, although they may vary according to investors (individuals, institutions, or market makers) and trade size. Data for bid-ask spreads (also known as execution costs, liquidity costs, or slippage costs), however, have not been widely available until recent years. To account for the impact of the bid-ask spread on asset returns, various bid-ask spread estimators were introduced by Roll (1984), Thompson and Waller (1987), and Smith and Whaley (1994). However, these estimators may not work particularly well in approximating the actual ex post bid-ask spreads if the assumptions underlying the estimators do not correspond to the actual market microstructure (Locke and Venkatesh 1997).[27] Although data for calculating actual bid-ask spreads generally is not publicly available, obtaining the relevant dataset seems to be of particular importance for the accurate estimation of bid-ask spreads. It is especially important because such data would reflect market-impact effects, or the effect of trade size on market price. Market-impact arises in the form of price concession for large trades (Fleming, Ostdiek, and Whaley 1996). A larger trade tends to move the bid price downward and move the ask price upward. The magnitude of market-impact depends on the liquidity and depth of a market.[28] The more liquid and deeper a market is, the less the magnitude of the market-impact. In addition to obtaining appropriate data sources regarding bid-ask spreads, either using transaction costs much greater than the actual historical commissions (Schwager 1996) or

[27] Using the Commodity Futures Trading Commission (CFTC) audit trail transaction records (complete trade history), Locke and Venkatesh (1997) estimated the actual transaction costs of 12 futures contracts, which were measured by the difference between the average purchase price and the average sale price for all customers including market makers and floor brokers, with prices weighted by trade size. They found that the actual transaction costs were generally lower than the minimum price changes (tick) or customer-market maker spreads, with the exception of several currency futures.

[28] Hausman, Lo, and MacKinlay (1992) quantified the magnitude of market-impact in the stock market by applying the ordered probit model to transactions data from the Institute for the Study of Security Markets (ISSM).

assuming several possible scenarios for transaction costs may be considered as plausible alternatives.

Other aspects of market microstructure that may affect technical trading returns are nonsynchronous trading and daily price limits, if any. Many technical trading studies assume that trades can be executed at closing prices on the day when trading signals are generated. However, Day and Wang (2002), who investigated the impact of nonsynchronous trading on technical trading returns estimated from the DJIA data, argued that "… if buy signals tend to occur when the closing level of the DJIA is less than the true index level, estimated profits will be overstated by the convergence of closing prices to their true values at the market open" (p. 433). This problem may be mitigated by using either the estimated 'true' closing levels for any asset prices (Day and Wang 2002) or the next day's closing prices (Bessembinder and Chan 1998). On the other hand, price movements are occasionally locked at the daily allowable limits, particularly in futures markets. Since trend-following trading rules typically generate buy (sell) signals in up (down) trends, the daily price limits enforce buy (sell) trades to be executed at higher (lower) prices than those at which trading signals were generated. This may results in seriously overstated trading returns. Thus, researchers should incorporate accurate daily price limits into the trading model. Many issues with respect to market microstructure including ones mentioned above are now being resolved with the advent of detailed transactions databases including transaction price, time of trade, volume, bid-ask quotes and depths, and various codes describing the trade (Campbell, Lo, and MacKinlay 1997, p. 107).

In conclusion, we found consistent evidence that simple technical trading strategies were profitable in a variety of speculative markets at least until the early 1990s. As discussed above, however, most previous studies are subject to various problems in their testing procedures. Future research must address these problems in testing before conclusive evidence on the profitability of technical trading strategies is provided.

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Figure 1 Number of technical trading studies (1960-2004)

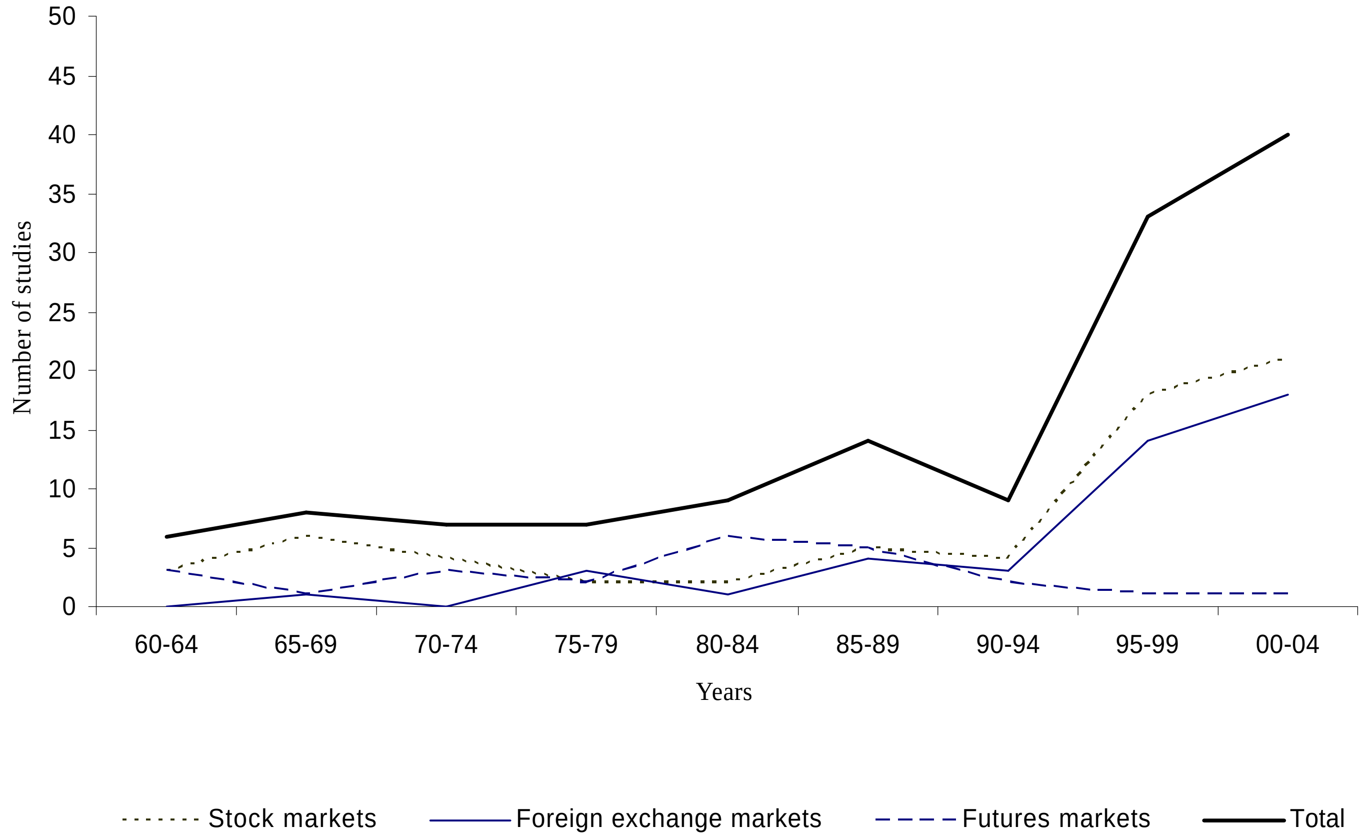

Table 1 Summary of early technical analysis studies published between 1961 and 1987

Criteria: Study	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
1. Donchian (1960)	Copper futures / Daily	1959-60	Channel	Not considered	$51.50 per round-trip	The current price was compared to the two preceding week's ranges. This trading rule generated net gains of $3,488 and $1,390, on margin of $1,000, for a single contract of the December 1959 delivery of copper and the December 1960 delivery, respectively.
2. Alexander (1961)	S&P Industrials, Dow Jones Industrials / Daily	1897-1959, 1929-59	Filter (11 rules from 5.0 to 50%)	Buy & hold	Not adjusted	Trading rules with 5, 6, and 8% filters generated larger gross profits than the B&H (buy-and-hold) strategy. All the profits were not likely to be eliminated by commissions. This led Alexander to conclude that there were trends in stock market prices.
3. Houthakker (1961)	Wheat and corn futures / Daily	1921-39, 1947-56	Stop-loss order (11 rules from 0 to 100%)	Buy & hold, Sell & hold	Not adjusted	Most stop-loss orders generated higher profits than the B&H or a sell and hold strategy. Long transactions indicated better performance than short transactions.
4. Cootner (1962)	45 NYSE stocks / Weekly	1956-60	Moving average (1/200 days with and without a 5% band)	Buy & hold	Commissions of 1% per one-way transaction	Although net returns from moving average rules were not much different from those from the B&H strategy, long transactions generated higher returns than the B&H strategy. Moreover, the variance of the trading rule was 30% less than that of the B&H.
5. Gray & Nielsen (1963)	Wheat futures / Daily	1921-43, 1949-62	Stop-loss order (10 rules from 1 to 100%)	Buy & hold, Sell & hold	Not adjusted	When applying stop-loss order rules to dominant contracts, there was little evidence of non-randomness in wheat futures prices. They argued that Houthakker's results were biased because he used remote contracts and that post-war seasonality of wheat futures prices was induced by government loan programs.
6. Alexander (1964)	S&P Industrials / Daily	1928-61	Filter, Formula Dazhi, Formala Dafilt, moving average, and Dow-type formulas	Buy & hold	Commissions of 2% for each round-trip	After commissions, only the largest filter (45.6%) rule beat the B&H strategy by a substantial margin. Most of the other trading systems earned higher gross profits than filter rules or the B&H strategy. However, after commissions they could not beat the B&H.
7. Smidt (1965a)	May soybean futures contracts / Daily	1952-61	Momentum oscillator (40 rules)	Not considered	$0.36 per bushel per round-trip	About 70% of trading rules tested generated positive returns after commissions. Moreover, half of trading rules returned 7.5% per year or more.
8. Fama & Blume (1966)	30 individual stocks of the DJIA / Daily	1956-62	Filter (24 rules from 0.5 to 50%)	Buy & hold	0.1% per round-trip plus other costs	After commissions, only 4 of 30 securities had positive average returns per filter. Even before commissions, filter rules were inferior to the B&H strategy for all but two securities. Although three small filter rules (0.5, 1.0, and 1.5%) earned higher gross average returns (11.4%-20.9% per year) per security when considering only long positions, net returns after transaction costs were not much different from B&H returns.

Table 1 continued.

Study / Criteria:	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
9. Levy (1967a)	200 NYSE stocks / Weekly	1960-65	Relative strength (Ratios: 1/4 and 1/26 weeks)	Geometric average	1% per one-way transaction	Net returns of several well-performing rules were nearly two or three times the return of the geometric average, although these rules possessed slightly higher standard deviations relative to the geometric average.
10. Levy (1967b)	200 NYSE stocks / Weekly	1960-65	Relative strength (Ratio: 1/26 weeks)	Not considered	1% per one-way transaction	Stocks having the historically strongest relative strength showed an average price appreciation of 9.6% over 26 weeks (about 20.1% per year). An annual price appreciation of all stocks was 12.8%. In general, stocks that had been both relatively strong and relatively volatile produced higher profits.
11. Poole (1967)	9 exchange rates / Daily	1919-29, 1950-62	Filter (10 rules from 0.1 to 2%)	Buy & hold	Not adjusted	Four of nine exchange rates had average annual gross returns more than 25% for the best filter rules, and three of them (Belgium, France, and Italy) generated returns above 44%. Filter rules beat the B&H strategy by large differences in returns.
12. Van Horne & Parker (1967)	30 NYSE stocks / Daily	1960-66	Moving average (100, 150, and 200 days with 0, 2, 5, 10, and 15% bands)	Buy & hold	Commissions charged by members of the NYSE	No trading rule earned a total closing balance nearly as large as that generated under the B&H strategy. Even before transaction costs, gross profits from each moving average rule were less than that from the B&H.
13. James (1968)	232 to 1376 stocks from the CRSP at the Univ. of Chicago / Monthly	1926-60	Moving average (7 months = 200 days with 2 and 5% bands)	Buy & hold	Not adjusted	Moving average rules could not beat the B&H strategy. The largest average dollar difference between the moving average rules and the B&H strategy was very small.
14. Van Horne & Parker (1968)	30 NYSE stocks / Daily	1960-66	Non-weighted and exponentially weighted moving averages (200 days with 0, 5, 10, and 15% bands)	Buy & hold	1% per one-way transaction	When applying trading rules to long positions, only 55 of 480 cases (16 different combinations of rules multiplied by 30 stocks) realized profits greater than those from the B&H strategy. For long plus short positions, a smaller number of trading rules (36 out of 480 cases) outperformed the B&H.
15. Jensen & Benington (1970)	29 portfolio samples of 200 NYSE stocks / Monthly	1931-65	Relative strength (2 rules from Levy (1967a))	Buy & hold	Actual round lot rate	After transaction costs, Levy's trading rules did not perform better than the B&H strategy. In fact, after explicit adjustment for the level of risk, the trading rules on average generated net returns less than the risk-adjusted B&H returns.

Table 1 continued.

Study	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
16. Stevenson & Bear (1970)	July corn and soybean futures / Daily	1957-68	Stop-loss order, filter, and combination of both systems	Buy & hold	0.5 cents per bushel for both commodities	For all systems, a 5% filter rule worked best, which generated larger net profits or greatly reduced losses relative to the B&H strategy. The filter rule also outperformed B&H for both corn and soybean futures.
17. Dryden (1970a)	U.K. stock indices, Tesco Stores stock / Daily	1962-67, 1962-64	Filter (12 rules from 0.1 to 5%)	Buy & hold	Individual stock: 0.625% per one-way transaction	Without transaction costs, filter rules consistently beat the B&H strategy for both indices and an individual stock. With transaction costs, the returns from the best filter rules were similar to those from the B&H, but long transactions beat the B&H.
18. Dryden (1970b)	15 U.K. stocks / Daily	1963-64, 1966-67	Filter (14 rules from 0.2 to 6%)	Buy & hold	Not adjusted	There was considerable variation among individual stocks' returns. On average, filter returns were less than the corresponding B&H returns except for two smallest filter rules. However, returns only from long transactions were much higher than the B&H returns.
19. Levy (1971)	548 NYSE stocks / Daily	1964-69	32 forms of a five-point chart pattern	Buy & hold	2% per round-trip	After transaction costs, none of the 32 patterns for any holding period generated profits greater than average purchase or short-sale opportunities. Even the best-performing pattern produced adjusted relative-to-market returns of -1.1% and -0.1% for one-week and 4-week holding periods, respectively.
20. Leuthold (1972)	30 live cattle futures contracts / Daily	1965-70	Filter (1, 2, 3, 4, 5, and 10%)	Not considered	Commissions of $36 per round-trip	Four of six filters were profitable after transaction costs. In particular, a 3% filter rule generated an annual net return of 115.8% during the sample period.
21. Martell & Philippatos (1974)	September wheat and September soybean futures contracts / Daily	1956-69 (1958-70)*	Adaptive filter model and pure information model	Buy & hold / Optimized trading rules	Adjusted but not specified	As an optimal filter size for period t, the adaptive model utilizes a filter size which has yielded the highest profits in t-1, subject to some minimum value of the average relative information gain. The pure information model chooses as an optimal filter size in period t the one with the highest relative average information gain in period t-1. Both models yielded higher net returns than the B&H only for wheat futures. However, the variance in net profits was consistently smaller than that of the B&H in both markets.

* Years in parentheses indicate out-of-sample periods.

Table 1 continued.

Criteria: Study	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
22. Praetz (1975)	Sydney wool futures / Daily	1965-72	Filter (24 rules from 0.5 to 25%)	Buy & hold	Not adjusted	For 12 of all 21 contracts of 18-month length and all three 8-year price series, the B&H strategy showed better performance than filter rules, with average differences of 0.1% and 2%, respectively. For the same data set, in 10 of 24 filters the B&H returns were greater than average filter returns. Thus, filter rules did not seem to outperform the B&H strategy consistently.
23. Martell (1976)	September wheat and September soybean futures contracts / Daily	1956-69 (1958-70)*	Adaptive filter models and pure information model	Buy & hold / Optimized trading rules	Adjusted but not specified	A new adaptive model was developed and applied to the same data set as that used in Martell and Philippatos (1974). The new model selects its optimal filter size for next period based on profitability (e.g., the highest cumulative net profits) and information gain. Although the model outperformed the previous adaptive model for around 80% of the sample period, it neither indicated any stability with respect to the information constraint nor beat the pure information model that allows a filter size in a particular period to reflect new information.
24. Akemann & Keller (1977)	Industry groups from S&P 500 Stock Index / Weekly	1967-75	Relative strength	S&P 500 Index	2% per round-trip	The relative strength rule is designed to buy the strongest stock group in a given thirteen-week period and sell it after 52 weeks. After adjustment for transaction costs, the mean return differential between all 378 possible trials and the market index appeared to be 14.6%, although the differentials were quite volatile.
25. Logue & Sweeney (1977)	Franc/dollar spot exchange rate / Daily	1970-74	Filter (14 rules from 0.7 to 5%)	Buy & hold	0.06% per one-way transaction	Most trading rules (13 out of 14 rules) outperformed the B&H strategy after considering transaction costs. Compared to the buy and hold and invest in French government securities strategy, only four filters failed to generate higher profits.
26. Cornell & Dietrich (1978)	6 spot foreign currencies (mark, pound, yen, Canadian dollar, Swiss franc, and Dutch guilder) / Daily	1973-75	Filter (13 rules from 0.1 to 5%), and moving average (10, 25, and 50 days with 0.1 to 2% bands)	Buy & hold	Computed by using the average bid-ask spread for all trades.	For the Dutch guilder, German mark, and Swiss franc, the best rules from each trading system generated over 10% annual net returns. Although the net returns were relatively small (1% to 4%) for the British pound, Canadian dollar, and Japanese yen, they all beat the B&H strategy. Moreover, since none of the systematic risk (beta) estimates exceeded 0.12, high returns of the three currencies were less likely to be compensation for bearing systematic risk.
27. Logue, Sweeney, & Willett (1978)	7 foreign exchange rates / Daily	1973-76	Filter (11 rules from 0.5 to 15%)	Buy & hold	Not adjusted	For every exchange rate (the mark, pound, yen, lira, France franc, Swiss franc, and Dutch guilder), profits from the best filter rules exceeded those from the B&H strategy by differences ranging from 9.3% to 32.9%.

* Years in parentheses indicate out-of-sample periods.

Table 1 continued.

Criteria: Study	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
28. Arnott (1979)	500 stocks from both the S&P 500 Index and the NYSE Composite Index / Weekly	1968-77	Beta-modified relative strength	Not considered	Not adjusted	Regression results indicated that for the base periods of 1 week to 18 weeks, the correlation between the change in (beta-adjusted) relative strength during the base period and that during any subsequent period was strongly negative. Hence, careless use of relative strength might lead to serious money loss.
29. Dale & Workman (1980)	90-day T-bill futures at the IMM / Daily	1976-78	Moving average (11 rules from 5 to 60 days)	Not considered	$60 per round-trip	For each individual contract, the best trading rules generated positive net returns, although the rules did not indicate consistent performances over the sample period.
30. Bohan (1981)	87 to 110 S&P industry groups / Weekly	1969-80	Relative strength	Buy & hold on S&P 500 Index	2% per year	There was a strong correlation between the performance of the strongest and weakest industry groups in one year and that of the following years, although the performance of the other groups did not have much predictive significance. For example, quintile 1 portfolio, which consists of the top 20% of industry groups, generated a return of 76% higher than the B&H on the market index, while the market outperformed quintile 5 portfolio by 80%.
31. Solt & Swanson (1981)	Gold from London Gold Market and silver from Handy & Harman / Weekly	1971-79	Filter (0.5 to 50%) and moving average (26, 52, and 104 weeks with filters)	Buy & hold	1.0% per one-way transaction plus 0.5% annual fees	For gold, a 10% filter rule outperformed the B&H strategy after adjustment for transaction costs. However, none of the filter rules dominated the B&H strategy for either gold or silver. Moving average rules were not able to improve the returns for the filter rules as well.
32. Peterson & Leuthold (1982)	7 hog futures contracts from CME / Daily	1973-77	Filter (10 rules from 1 to 10% and additional 10 rules from $0.5 to $5)	Zero mean profit	Not adjusted	All 20 filter rules produced considerable mean gross profits. It seemed that these profit levels exceeded any reasonable commission charges in most cases. In general, mean gross profits increased with larger filters, as did variance of profits.
33. Dooley & Shafer (1983)	9 foreign currencies in the New York market / Daily	1973-81	Filter (7 rules from 1 to 25%)	Not considered	Adjusted but not specified	Although results were slightly different for each currency, small filter rules (1, 3, and 5%) generally produced high profits, while larger filter rules showed consistent losses.

Table 1 continued.

Criteria: Study	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
34. Brush & Boles (1983)	168 S&P 500 stocks / Monthly	1967-80, (two data bases were used for out-of-sample tests)	Relative strength (parameters were optimized on the development data base over 26 separate 6-month test periods)	Equal-weighted 168-stock return / Optimized models	2% per round-trip	The top decile annualized excess return of the best model was 7.1% per year over the equal-weighted 168-stock return, after adjustment for risk, dividend yield, and transaction costs. The model also produced a compounded growth of 15.2% per year after considering dividend yield and transaction costs, compared to 5.9% for the S&P 500.
35. Irwin & Uhrig (1984)	8 commodity futures: corn, cocoa, soybeans, wheat, sugar, copper, live cattle, and live hogs / Daily	1960-78 (1979-81)*, 1960-68 (1969-72)*, 1973-78 (1979-81)*	Channel, moving averages, momentum oscillator	Zero mean profit / Optimized trading rules	Doubled commissions to capture bid-ask spread (not specified)	Trading rule profits during in-sample periods were substantial and similar across all four trading systems. Out-of-sample results for optimal trading rules also indicated that during the 1979-81 period most trading systems were profitable in corn, cocoa, sugar, and soybean futures markets. The trading rule profits appeared to be concentrated in the 1973-81 period.
36. Neftci & Policano (1984)	4 futures: copper, gold, soybeans, and T-bills / Daily	1975-80	Moving average (25, 50, and 100 days) and slope (trendline) method	Not considered	Not adjusted	Trading signals were incorporated as a dummy variable into a regression equation for the minimum mean square error prediction. Then the significance of the dummy variable was evaluated using F-tests. Overall, moving average rules indicated some predictive power for T-bills, gold, and soybeans, while the slope method showed mixed results.
37. Tomek & Querin (1984)	3 random price series (each series consists of 300 prices) generated from corn prices for each sample period / Daily	1975-80, 1973-74, 1980	Moving average (3/10 and 10/40 days)	Not considered	$50 per round-trip	From each of three random prices series, 20 sets of prices were replicated. The first 20 sets had moderate price variability, the second set large price variability, and the third set drift in prices. Both trading rules failed to generate positive average net profits for all three groups with an exception of the 10/40 rule for the relatively volatile price group. The results imply that technical trading rules may earn positive net returns by chance, although they on average could not generate positive net profits.
38. Bird (1985)	Cash and forward contracts of copper, lead, tin, and zinc from London Metal Exchange (LME) / Daily	1972-82	Filter: long positions (and cash profits) (25 rules from 1 to 25%)	Buy & hold	1% per round-trip	For cash and forward (futures) copper, over 2/3 of filter rules beat the B&H strategy. Similar results were obtained for lead and zinc but with weaker evidence. For tin, the results were inconsistent. Filter rules performed substantially better in the earlier period (1972-77).

* Years in parentheses indicate out-of-sample periods.

Table 1 continued.

Criteria: Study	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
39. Brush (1986)	420 S&P 500 stocks / Monthly	1969-84	Relative strength	Return of the equal-weighted S&P 500 Index	1% per round-trip	By avoiding the year-end effect and exploiting beta corrections and the negative predictive power of one-month trends, the best model, which was the generalized least squares beta approach, generated an annual excess return of more than 5% over the equal-weighted S&P 500, after transaction costs.
40. Sweeney (1986)	Dollar/mark and additional 9 exchange rates / Daily	1973-75 (1975-80)*	Filter: long positions (7 rules from 0.5 to 10%)	Buy & hold / Optimized trading rules	1/8 of 1% of asset value per round-trip	Both in- and out-of-sample tests, small filter rules (0.5% to 5%) consistently beat the B&H strategy, and transaction costs did not eliminate the risk-adjusted excess returns of filter rules. Eight filter rules across 6 exchange rates produced statistically significant excess returns over the B&H in both in- and out-of sample periods.
41. Taylor (1983, 1986)	London agricultural futures: cocoa, coffee, and sugar, Chicago IMM currency futures: sterling, mark, and Swiss franc / Daily	1971-76 (1977-81)*, 1961-73 (1974-81)*, 1974-78 (1979-81)*	A statistical price-trend model	Buy & hold and interest rate for bank deposit / Optimized trading rules	1% per round-trip for agricultural futures and 0.2% for currency futures	Taylor (1986) adds one more out-of-sample year (i.e., 1981) to the sample period in his 1983's work. For sugar, an average net return of the trading rule was higher than that of the B&H strategy by 27% per annum. For cocoa and coffee, returns from both the trading rule and the B&H were not much different. Trading gains for currencies during 1979-80 were negligible, but in 1981 all currencies generated substantial gains of around 7% higher than the bank deposit rate.
42. Thompson & Waller (1987)	Coffee and cocoa futures in the NY Coffee, Sugar, and Cocoa Exchange / 6 weekly sets of transaction-to-transaction prices for each market	1981-83	Filter (for coffee, 5¢ through 35¢ in multiples of 5¢ per 100 lb; for cocoa, $1 through $7 per metric ton)	Not considered	Estimated execution costs	For both nearby and distant coffee and cocoa contracts, filter rules generated average profits per trade per contract substantially lower than estimated execution costs per contract in all cases in which profits were statistically significantly greater than zero. The estimated execution costs per trade per contract were $32.25 (nearby) and $69.75 (distant) for coffee futures contracts and $12.60 (nearby) and $21.80 (distant) for cocoa futures contracts.

* Years in parentheses indicate out-of-sample periods.

Table 2 Categories for modern technical analysis studies

Category	Number of studies	Representative study	Criteria						Distinctive features
			Transaction costs	Risk adjustment	Trading rule optimization	Out-of-sample tests	Statistical tests	Data snooping addressed	
Standard	23	Lukac, Brorsen, & Irwin (1988)	v	v	v	v	v		Conduct parameter optimization and out-of-sample tests.
Model-based bootstrap	21	Brock, Lakonishok, & LeBaron (1992)		v			v		Use model-based bootstrap methods for statistical tests. No parameter optimization and out-of-sample tests conducted.
Genetic programming	11	Allen & Karjalainen (1999)	v	v	v	v	v	v	Use genetic programming techniques to optimize trading rules.
Reality Check	3	Sullivan, Timmermann, & White (1999)		v	v	v	v	v	Use White's Reality Check Bootstrap methodology for optimization and statistical tests.
Chart patterns	11	Chang & Osler (1999)	v	v			v		Use recognition algorithms for chart patterns.
Nonlinear	7	Gençay (1998a)	v	v	v	v	v		Use nearest neighbors and/or feedforward network regressions to generate trading signals.
Others	16	Neely (1997)	v	v			v		Most studies in this category lack trading rule optimization and out-of-sample tests, and do not address data-snooping problems.

Table 3 Summary of standard technical analysis studies published between 1988 and 2004

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
1. Lukac, Brorsen, & Irwin (1988)	12 futures from various exchanges: agriculturals, metals, currencies, and interest rates / Daily	1975-83 (1978-84)	12 systems (3 channels, 3 moving averages, 3 oscillators, 2 trailing stops, and a combination)	Zero mean profit / Optimized trading rules	$50 and $100 per round-trip	Out-of-sample results indicated that 4 of 12 systems generated significant aggregate portfolio net returns and 8 of the 12 commodities earned statistically significant net returns from more than one trading system. Mark, sugar, and corn markets appeared to be most profitable during the sample period. In addition, Jensen test confirmed that the same four trading systems having large net returns still produced significant net returns above risk.
2. Lukac & Brorsen (1989)	15 futures from various exchanges: agricultural commodities, metals, currencies, and interest rates / Daily	1965-85 (various)	Channel and directional movement (both systems had 12 parameters ranging 5 days to 60 days in increments of 5)	Buy & hold / Optimized trading rules	$100 per round-trip	Technical trading rule profits were measured based on various optimization methods, which included 10 re-optimization strategies, one random strategy, and 12 fixed parameter strategies. The two trading systems generated portfolio mean net returns significantly greater than the B&H strategy. However, the trading systems yielded similar profits across different optimization strategies and even different parameters. Thus, the parameter optimization appeared to have little value.
3. Sweeney & Surajaras (1989)	An equally-weighted portfolio and a variably-weighted portfolio of currencies / Daily	Prior 250- to 1400-day prices (1980-86)	Filter, single moving average, double moving average, and the best system	Buy & hold / Optimized trading rules	Adjusted but not specified	Most trading systems generated risk-adjusted mean net profits after transaction costs, and the single moving average rule performed best. The variably-weighted portfolio approach generally outperformed the equally-weighted approach. Changing neither parameters for each trading system on a yearly basis nor amounts of data used to select optimal parameters seem to improve trading profits.
4. Taylor & Tari (1989)	IMM currency futures: pound, mark, and Swiss franc; London agricultural futures: cocoa, coffee, and sugar / Daily	1974-78 (1979-87); (1982-85)	A statistical price-trend model	Buy & hold, Zero mean profit / Optimized trading rules	Currency futures: 0.2% per round-trip; Agricultural futures: 1%	During the out-of-sample period, 1979-87, the trading rule earned aggregate mean net return of 4.3% per year for three currency futures. The mark was the most profitable contract (5.4% per year). From 1982-85, the trading rule generated a mean net return of 4.8% for cocoa, -4.26% for coffee, and 18.8% for sugar, outperforming the B&H strategy for cocoa and sugar futures.
5. Lukac & Brorsen (1990)	30 futures from various exchanges: agriculturals, metals, oils, currencies, interest rates, and S&P 500 / Daily	1975-85 (1976-86)	23 systems (channels, moving averages, oscillators, trailing stops, point and figure, a counter-trend, volatility, and combinations)	Zero mean profit / Optimized trading rules	$50 and $100 per round-trip	Only 3 of 23 trading systems had negative mean monthly portfolio net returns after transaction costs, and 7 of 23 systems generated net returns significantly above zero at 10% level. Most of the trading profits appeared to be made over the 1979-80 period. In the individual commodity markets, currency futures produced the highest returns, while livestock futures yielded the lowest returns.

Table 3 continued.

Criteria: / Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
6. Taylor (1992)	4 currency futures from IMM of the CME: pound, mark, yen, and Swiss franc / Daily	1977-87 (1982-87)	3 technical trading systems (filter, channel, moving average), 2 statistical price-trend models	Buy & hold / Optimized trading rules	0.2% per round-trip	All trading rules outperformed the B&H strategy across all currency futures. Among trading rules, three technical trading systems and a revised statistical trend model generated statistically significant and much higher mean net returns (3.0% to 4.0%) than that (2.0%) of the original price-trend model for most currencies. These returns could not be explained by nonsynchronous trading or time-varying risk premia.
7. Farrell & Olszewski (1993)	S&P 500 futures / Daily	1982-90 (1989-90)	A nonlinear trading strategy based on ARMA (1,1) model and 3 trend-following systems (channel and volatility systems)	Buy & hold / Optimized trading rules	0.025% per round-trip	Although the nonlinear trading strategy were slightly more profitable than the B&H strategy, the result was statistically insignificant. For the in-sample period, the nonlinear optimal trading strategy was more profitable than the B&H by nearly 5%, while for the out-of-sample period, the trading strategy was better by 3%. Meanwhile, the three trend following strategies were more profitable than the nonlinear trading strategy by around 5% to 11% during the out-of-sample period, depending on the trading strategy.
8. Silber (1994)	12 futures markets: foreign currencies, short-term interest rates, metals, oil, and S&P 500 / Daily	1979 (1980-91)	Moving average (short averages: 1 day to 15 days; long averages: 16 to 200 days)	Buy & hold (& roll over) / Optimized trading rules	Bid-ask spreads per round-trip (2 ticks for crude oil and gold; 1 tick for the rest of contracts)	After transaction costs, average annual net returns were positive for all contracts but gold, silver, and the S&P 500. In particular, most currency futures earned higher net profits (1.9% to 9.8%). For those profitable markets, moving average rules beat the B&H strategy except for 3-month Eurodollars. Test results using a Sharpe ratio criterion were similar. Hence, trading profits appeared to be robust to transaction costs and risk. Central bank intervention is one of possible explanations for the trading profits.
9. Taylor (1994)	4 currency futures from IMM: pound, mark, yen, and Swiss franc / Daily	1980-all previous contracts (1982-90)	Channel	Zero mean profits / Optimized trading rules	0.2% per one-way transaction	For price series generated by ARIMA(1,1,1) model, channel rules correctly identified the sign of conditional expected returns with around 60% probability. During 1982-90, optimal channel rules produced an average net return of 6.9% per year. The t-test indicated that the return was significant at the 2.5% level. The best trading opportunities occurred for 1985-87.
10. Menkhoff & Schlumberger (1995)	3 spot exchange rates: mark/dollar, mark/yen, and mark/pound / Daily	1981-91, 1981-85 (1986-91)	Oscillator (33 moving averages) and momentum (10 rules from 5 to 40 days)	Buy & hold / Optimized trading rules	0.0008 DM for 1$; 0.0017 DM for 1 yen; 0.003 DM for 1 BP per round-trip	During the out-of-sample period, 84% out of 129 technical trading rules tested outperformed the B&H strategy across exchange rates, after adjustment for transaction costs and risk. However, superiority of optimal trading rules during the in-sample period deteriorated in the out-of-sample period, even though they still outperformed the B&H strategy.

Table 3 continued.

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
11. Lee & Mathur (1996a)	6 European currency spot cross-rates / Daily	1988-92 (1989-93)	Moving average (short moving averages: 1 day to 9 days; long moving averages: 10, 15, 20, 25, and 30 days)	Zero mean profits / Optimized trading rules	0.1% per round-trip	Results of in-sample tests indicated that the trading rules did not yield significantly positive returns for all cross rates but yen/mark and yen/Swiss franc (11.5% and 8.8% per year, respectively). Out-of-sample results were even worse. Most cross rates earned negative trading returns, although long positions for the yen/mark produced marginally significant positive returns.
12. Lee & Mathur (1996b)	10 spot cross-rates / Daily	1988-92 (1989-93)	Moving average (short moving averages: 1 day to 9 days; long moving averages: 10, 15, 20, 25, and 30 days) and channel (2 to 50 days)	Zero mean profits / Optimized trading rules	0.1% per round-trip	During in-sample periods, moving average rules in general produced negative or statistically insignificantly positive net returns except the mark/yen (11.5% per year) and the Swiss franc/yen (8.8% per year). Similar results were found for channel rules. During out-of-sample periods, overall returns of the trading rules were negative or statistically insignificantly positive. Only for the mark/lira, both long positions of moving average rules and channel rules generated statistically significant profits.
13. Szakmary & Mathur (1997)	5 IMM foreign currency futures and spots: mark, yen, pound, Swiss franc, and Canadian dollar / Daily	1977-90 (1978-91)	Moving average (short moving averages: 1 day to 9 days; long moving averages: 10, 15, 20, 25, and 30 days)	Zero mean profits / Optimized trading rules	0.1% per round-trip	In-sample results indicated that moving average rules generated both statistically and economically significant returns for all currency futures but the Canadian dollar. Similar results were reported for both out-of-sample data (annual net returns ranged from 5.5% to 9.6%) and spot rates. Further analyses showed that the moving average rule profits resulted from the central bank's "leaning against the wind intervention."
14. Goodacre, Bosher, & Dove (1999)	254 companies in the FTSE 350 Index and 64 option trades in the U.K. / Daily	Prior 200 days (1988-96)	CRISMA (combination system of **C**umulative volume, **R**elat**I**ve **S**trength, and **M**oving **A**verage)	FTSE All Share Index / Optimized parameters	0 to 2% per round-trip	The CRISMA trading system generated annualized profits ranging 6.9% to 19.3% depending on transaction costs, while an annualized return on the FTSE All Share Index over the same time period was 14.0%. When adjusted for market movements and risk, however, mean excess returns for nonzero levels of transaction costs were significantly negative. Moreover, performance of the trading system was not stable over time. With option trading, the system generated mean return of 10.2% per trade even in the presence of maximum retail costs, but only 55% of trades were profitable.
15. Kwan, Lam, So, & Yu (2000)	Hang Seng Index Futures / Daily	1986-97 (1990-98)	A statistical price-trend model	Buy & hold / Optimized parameters	0.4 to 0.5% per one-way transaction	The price-trend model performed poorer than the B&H strategy in the periods 1991-93 and 1995-96 when the market was bullish. However, the trading rule produced larger profits than the B&H in the years, 90, 94, 97, and 98 when the market became up and down. Across all years and transaction costs considered, an average net return (10.1%) of the trading rule was slightly smaller than that (13.5%) of the B&H strategy.

Table 3 continued.

Study (Criteria:)	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
16. Maillet & Michel (2000)	12 exchange rates (combinations of U.S. dollar, mark, yen, pound, and France franc) / Daily	1974-79 (1979-96)	Moving average (short moving averages: 1 day to 14 days; long moving averages: 15 to 200 days)	Zero mean profits, buy & hold / Optimized trading rules	Not adjusted	Optimized moving average rules generated statistically significant returns and outperformed the corresponding B&H strategies with the exception of the mark/franc rate. Bootstrap tests generally confirmed the results with the rejection of higher returns only in 4 out of 12 rates: the mark/dollar, mark/franc, yen/dollar, and yen/franc. Moreover, riskiness of both moving average rules and the B&H strategy, which was measured by their standard deviations, appeared to be not much different.
17. Taylor (2000)	1) Financial Times (FT) All-Share index; 2) UK 12-share index; 3) 12 UK stocks; 4) FT 100 index and index futures; 5) DJIA index; 6) S&P 500 index and index futures / Daily	1), 2), and 3): 1972-91; 4): 1985-94; 5): 1897-1988; 6): 1982-92	Moving average (short moving averages: 1, 2, and 5 days; long moving averages: 50, 100, 150, and 200, with and without a 1% band)	/ Parameters are optimized for the DJIA data from 1897 to 1968.	Not adjusted	The results of optimized moving average rules indicated that differences of mean returns between buy and sell positions were substantially positive and statistically significant for the FTA index, all versions of the 12-share index, 4 of the 12 UK firms, and the DJIA index for 3 out of 5 subperiods. No significant results were found for the FTSE 100 and S&P 500 indices. Buy positions also appeared to have lower standard deviations than sell positions for all but two series. An average breakeven one-way transaction cost across all data series was 0.35%. In particular, for the DJIA index, a trading rule (a 5/200 moving average rule) optimized over the 1897-1968 period produced a breakeven one-way transaction cost of 1.07% during the 1968-88 period.
18. Goodacre & Kohn-Spreyer (2001)	A random sample of 322 companies from the S&P 500 / Daily	Prior 200 days (1988-96)	CRISMA (combination system of **C**umulative volume, **R**elat**I**ve **S**trength, and **M**oving **A**verage)	The S&P 500 Index / Optimized parameters	0 to 2% per round-trip	The CRISMA system generated annualized profits ranging 6.2% to 17.6% depending on transaction costs, while the annualized return on the S&P 500 Index over the same time period was 14.2%. However, when adjusted for market movements and risk, mean excess returns for nonzero levels of transaction costs were significantly negative across all return-generating models. Moreover, the results were not stable over time, although trades on larger firms generally performed better than small ones.
19. Lee, Gleason, & Mathur (2001)	13 Latin American spot currencies / Daily	1992-99 (various periods from data available)	Moving average (short moving averages: 1 day to 9 days; long moving averages: 10 to 30 days) and channel (2 to 50 days)	Zero mean profits / Optimized trading rules	0.1% per round-trip	Out-of-sample results showed that moving average rules generated significantly positive returns for currencies of four countries: Brazil, Mexico, Peru, and Venezuela. Channel rules also produced significant profits for the same currencies except that of Peru. When only long positions were considered, there was a marginal improvement to five and four currencies for moving average rules and channel rules, respectively.

Table 3 continued.

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
20. Lee, Pan, & Liu (2001)	9 exchange rates from Asian countries	1988-94 (1989-95)	The same trading rules as in Lee, Gleason, & Mathur (2001)	Zero mean profits / Optimized trading rules	0.1% per round-trip	Out-of-sample tests indicated that four exchange rates from Korea, New Zealand, Singapore, and Taiwan yielded positive profits for both moving average rules and channel rules. However, these profits were not significantly different from zero, except that of the Taiwan dollar.
21. Martin (2001)	12 currencies in developing countries / Daily	1/92-6/92 (7/92-6/95)	Moving average (short moving averages: 1 day to 9 days; long moving averages: 10 to 30 days)	Short-selling strategy / Optimized trading rules	0.5% per one-way transaction	Out-of-sample, moving average rules generated positive mean net returns in 10 of 12 currencies, and the returns were greater than 0.14% daily (35% per year) in 5 currencies. However, Sharpe ratios indicated that moving average rules did not generate superior returns on a risk-adjusted basis.
22. Skouras (2001)	Dow Jones Industrial Average (DJIA) / Daily	1962-86 (1962-86)	Moving average (2 to 200 days with bands of 0, 0.5, 1, 1.5, and 2%)	Buy & hold / Optimized trading rules	Various levels from 0 to 0.1% per one-way transaction	Out-of-sample returns were estimated on a daily basis. Time-varying estimated rules (by an Artificial Technical Analyst) outperformed various fixed moving average rules employed by Brock et al. (1992) as well as the B&H strategy. When considering transaction costs, however, mean returns from the optimized trading rule were higher than the B&H mean return only after transaction costs of less than 0.06%.
23. Olson (2004)	18 exchange rates / Daily	5-year in-sample period from 1971-2000 (1976-2000)	Moving average (short moving averages: 1 day to 12 days; long moving averages: 5 to 200 days)	Buy & hold / Optimized trading rules	0.1% per round-trip	Out-of-sample results indicated that risk-adjusted trading profits for individual currencies and an equal-weighted 18-currency portfolio declined over time. For the 18-currency portfolio, annualized risk-adjusted returns decreased from an average of over 3% in the late 1970s and early 1980s to about zero percent in the late 1990s. Overall, profits of moving average rules in foreign exchange markets have declined over time.

Table 4 Summary of model-based bootstrap technical analysis studies published between 1988 and 2004

Criteria: Study	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
1. Brock, Lakonishok, & LeBaron (1992)	Dow Jones Industrial Average (DJIA) / Daily	1897-1986	Moving averages (1/50, 1/150, 5/150, 1/200, and 2/200 days with 0 and 1% bands) and trading range breakout (50, 150 and 200 days with 0 and 1% bands)	Unconditional 1- and 10-day returns	Not adjusted	Before transaction costs, buy (sell) positions across all trading rules consistently generated higher (lower) mean returns than unconditional mean returns, and these results were highly significant in most cases. For example, a mean buy return from variable moving average rules was about 12% per year and a mean sell return was about -7%. Moreover, the buy returns were even less volatile than the sell returns. Simulated series from a random walk with a drift, AR (1), GARCH-M, and EGARCH models using a bootstrap method could not explain returns and volatility of the actual Dow series.
2. Levich & Thomas (1993)	5 IMM currency futures: mark, yen, pound, Canadian dollar, and Swiss franc / Daily	1976-90	Filters (0.5, 1, 2, 3, 4, and 5%) and moving average (1/5, 5/20, 1/200 days)	Buy & hold	0.025% and 0.04% per one-way transaction	After adjustment for transaction costs and risk, every filter rule and moving average rule generated substantial positive mean net returns for all currencies but the Canadian dollar. Moreover, the results of the bootstrap simulation indicated that, for both trading systems, the null hypothesis that there is no information in the original time series was rejected in 25 of 30 cases.
3. Bessembinder & Chan (1995)	Asian stock indices: Hong Kong, Japan, Korea, Malaysia, Thailand, and Taiwan / Daily	1975-91	The same trading rules as in Brock et al. (1992)	Buy & hold	0.5, 1, and 2% per round-trip	Across all markets and trading rules tested, average mean returns on buy days exceeded those on sell days by 26.8% per year, and an average break-even round-trip transaction cost for the full sample was 1.57%. In particular, technical signals generated by the U.S. markets appeared to have substantial forecast power for returns in the Asian markets. Overall, trading rules generated higher net profits (12.2% to 21.2% per year) in the Malaysia, Thailand, and Taiwan stock markets.
4. Hudson, Dempsey, & Keasey (1996)	Financial Times Industrial Ordinary Index (FT30) in the U.K. / Daily	1935-94	The same trading rules as in Brock et al. (1992)	Unconditional mean returns	More than 1% per round-trip for large investing institutions	Before transaction costs, buy (sell) positions across all trading systems consistently generated higher (lower) returns than unconditional returns. However, an extra return per round-trip transaction averaged across all systems appeared to be about 0.8%, which was relatively smaller than the round-trip transaction costs of 1%.
5. Kho (1996)	4 currency futures from IMM: pound, mark, yen, and Swiss franc / Weekly	1980-91	Moving average (1/20, 1/30, 1/50, 2/20, 2/30, 2/50 weeks with bands of 0 and 1%)	Unconditional weekly mean return, Univariate GARCH-M	Not adjusted	Initially, moving average rules generated substantial mean returns between 9.9% and 11.1% per year from buy signals. These trading returns could not be explained by the empirical distribution of the univariate GARCH-M model as well as transaction costs or serial correlations in futures returns. However, the returns appeared to be insignificant when time-varying risk premia, which were estimated from a general model of the conditional CAPM, were taken into account.

Table 4 continued.

Criteria: Study	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
6. Raj & Thurston (1996)	Hang Seng Futures Index of Hong Kong / Daily	1989-93	The same trading rules as in Brock et al. (1992), without 1/150 and 2/200 moving average rules	Unconditional mean returns	Not adjusted	Without considering transaction costs, average buy returns generated from both trading systems were much higher than the unconditional one-day mean. In particular, the trading range breakout system generated significantly higher annual returns (457% to 781%) in four out of six rules relative to that (39%) of the B&H strategy. On the other hand, average sell returns obtained from both systems were negative.
7. Mills (1997)	Financial Times–Institute of Actuaries 30 (FT30) index in the London Stock Exchange / Daily	1935-94: 1935-54, 1955-74, 1975-94	The same trading rules as in Brock et al. (1992)	Unconditional mean daily return	Not adjusted	For moving average rules, each mean daily buy-sell return difference (0.081% and 0.097%) for 1935-54 and 1955-74 was much greater than corresponding unconditional mean returns (0.013% and 0%). For the latest subperiod, 1975-94, however, the mean buy-sell difference was insignificantly different from the unconditional return. Trading range breakout rules showed similar results. None of simulated series generated by AR-ARCH bootstraps earned mean buy-sell differences larger than the actual difference.
8. Bessembinder & Chan (1998)	Dow Jones Industrial Average (DJIA) / Daily	1926-91: 1926-43, 1944-59, 1960-75, 1976-91	The same trading rules as in Brock et al. (1992)	Buy & hold	Various estimates for NYSE stocks	The DJIA data in this study includes dividend payments. Over the full sample period, an average buy-sell return difference across all 26 trading rules was 4.7%, generating a break-even one-way transaction cost of 0.39%. However, break-even transaction costs have declined over time with 0.22% for the most recent subperiod (1976-91). It was compared with an estimated transaction cost of 0.25%.
9. Ito (1999)	6 national equity market indices (Japan, U.S. Canada, Indonesia, Mexico, Taiwan), Dow Jones index, Nikkei index futures / Daily	1980-96 for developed markets, 1988-96 for emerging markets	The same trading rules as in Brock et al. (1992)	Buy & hold	Nikkei index futures: 0.11% per round-trip; other equity indices: 0.69-2.21%	After transaction costs, technical trading rules outperformed the B&H strategy for all indices but U.S. indices, and generated higher profits for emerging markets (Indonesia, Mexico, Taiwan) than for developed markets. The trading profits could not be explained by nonsynchronous trading. However, some conditional asset pricing models (in particular, the asset pricing model under mild segmentation) were able to explain trading rule profits for Japan, the U.S., the second subperiod of Canada, and Taiwan stock indices. These results suggest that technical trading profits were a fair compensation for risk of trading rules.
10. LeBaron (1999)	2 foreign currencies from the London close: mark and yen / Daily and weekly	1979-92	Moving average (1/150 days or 1/30 weeks)	Sharpe ratio for buying and holding on U.S. stock portfolios	Commissions (0 to 0.5%) and bid-ask spread (0.15%) per round-trip	Mean returns of the trading rule for the two currencies were statistically significantly different from zero. Their Sharpe ratios (0.60 to 0.98) were also higher than those (0.3 or 0.4) for the B&H on U.S. stock portfolios even after adjustment for a transaction cost of 0.1% per round-trip. In general, interest differentials and transaction costs did not alter the result greatly. However, trading returns were dramatically reduced when active intervention periods of the Federal Reserve were eliminated.

Table 4 continued.

Criteria: Study	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
11. Ratner & Leal (1999)	10 equity indices in Asia and Latin America / Daily	1982-95	Moving average (1/50, 1/150, 5/150, 1/200, and 2/200 days with bands of zero and one standard deviation)	Buy & hold	Various costs from 0.15 to 2.0% per one-way transaction	After transaction costs, 21 out of 100 trading rules that were applied to the 10 indexes generated statistically significant returns (18.2% to 32.1% per year), with the profitability concentrated in four markets: Mexico, Taiwan, Thailand, and the Philippines. When statistical significance was ignored, however, 82 out of the 100 rules appeared to have forecasting ability in emerging markets.
12. Coutts & Cheung (2000)	Hang Seng Index on the Hong Kong Stock Exchange / Daily	1985-97	The same trading rules as in Brock et al. (1992)	Unconditional mean returns	Not adjusted	Across all trading rules tested, buy (sell) signals generated significantly higher (lower) mean returns than unconditional mean returns. In particular, buy (sell) signals of the trading range breakout system earned substantial average 10-day cumulative return of 1.6% (-5%), which was higher (lower) than that of the moving average system.
13. Parisi & Vasquez (2000)	Santiago stock index / Daily	1987-98	The same trading rules as in Brock et al. (1992)	Unconditional mean returns	1% per one-way transaction	Across trading rules, mean returns on buy signals were consistently higher than those on sell signals or unconditional mean returns. In fact, sell signals yielded negative mean returns for most trading rules. Although variable-length moving average rules generated significant returns, it was unlikely that these rules were profitable if high transaction costs were taken into account.
14. Raj (2000)	Yen and mark traded in Singapore International Monetary Exchange / Intra-daily	01/1992-12/1993	Filter, moving average, and channel	Buy & hold	0.04% per one-way transaction	None of technical trading rules except one rule (2/200 moving average rule with a 1% band) generated statistically significant returns after adjustment for transaction costs and risk. However, some trading rules appeared to produce economically significant returns. For instance, for the mark a 1/50 moving average rule with a 1% band generated a risk-adjusted net return of 8.8% over the two-year period.
15. Gunasekarage & Power (2001)	4 South Asian stock indices: Bombay, Colombo, Dhaka, and Karachi stock exchanges / Daily	1990-2000	Moving averages (1/50, 1/100, 1/150, 1/200, 2/100, 2/150, 2/200, 5/200, and 1/50 with 1% band)	Buy & hold	Not adjusted	For variable moving average rules, buy signals generated positive returns of more than 44.2% per year and sell signals generated negative returns of less than -20.8% per year. These returns, on average, were significantly different from the B&H returns. Similar results were obtained for fixed-length moving average rules with 10-day holding periods.

Table 4 continued.

Criteria: Study	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
16. Day & Wang (2002)	Dow Jones Industrial Average (DJIA) / Daily	1962-96	Moving average (1/50 and 1/150 days with 0 and 1% bands) and trading range breakout (50 and 150 days with 0 and 1% bands)	Buy & hold	0.05% per one-way transaction	Variable-length moving average rules generated daily excess returns of more than 0.027% over the B&H strategy for 1962-86, and all the returns were statistically significant. For closing levels of the DJIA that were estimated to reduce the effects of nonsynchronous trading, the trading rules also outperformed the B&H, although returns were reduced relative to previous ones and not all were statistically significant. For 1987-96, however, the performance of the trading rules was inferior to the B&H strategy in most cases.
17. Kwon & Kish (2002)	The NYSE value-weighted index / Daily	1962-96: 1962-72, 1973-84, 1985-96	Moving average, combination of moving average and momentum, and combination of moving averages for price and volume	Unconditional mean returns	Not adjusted	Combination moving average rules of price and volume generated the highest daily average return of 0.13% over the full sample period. Across all subperiods but the recent 1985-96 period, returns of the trading system were statistically significantly different from unconditional mean returns. Similar results were obtained for the other two trading systems. Simulated series from three popular models (random walk, GARCH-M, and GARCH-M with instrument variable) could not explain returns and volatility of the technical trading systems.
18. Neely (2002)	4 foreign exchange rates: mark, yen, Swiss franc, and Australia dollar / Intra-daily and daily	1983-98	Moving average (1/150)	Not considered	Not adjusted	With daily data, the moving average rule generated positive annual mean returns for all series ranging from 2.4% for the Australian dollar to 8.7% for the yen. However, when intervention periods of central banks were removed, the trading rule returns were greatly reduced, ranging from –2.3% to 4.5%. With intra-daily data, the highest US, Swiss, and German excess returns appeared to precede business hours and thus precede intervention. Hence, intervention was less likely to be a cause that generated trading rule profits.
19. Saacke (2002)	Dollar/mark exchange rate in the New York market / Daily	1979-94	Moving average (2 to 500 days)	Not considered	0.05% per round-trip	Moving average rules below 170 days earned positive net returns. Bootstrapping simulations based on a random walk with drift and a GARCH model could not account for the size of trading rule returns. Moving average rules appeared to be highly profitable on days when central banks intervened. However, since trading rule returns in periods that neither coincided with nor were preceded by interventions were also sizable, interventions did not seem to be the only cause of the trading rule profitability.

Table 4 continued.

Criteria: Study	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
20. Fang & Xu (2003)	3 Dow Jones Indexes (Industrial, Transportation, and Utilities Averages) / Daily	1896-1996	Moving average, time series models, and combination of moving average and time series models	Buy & hold	Various estimates	When the market was bullish (bearish), technical trading rules performed in general better (worse) than trading strategies based on time series models. When a monthly interest rate of 0.30% was assumed over the full sample period, combination rules produced average break-even transaction costs of about 1.01%, 1.96%, and 1.76% for the Industrial, Transportation, and Utilities Averages, respectively, with non-synchronous trading adjustment. These figures appeared to be substantial improvement on those of moving average rules (0.60%, 0.84%, and 0.80%, respectively).
21. Sapp (2004)	Mark and yen / Daily	1975-1998	Moving average	Sharpe ratio for S&P500	Bid-ask spread	During the 1980-94 period, moving average rules generated statistically and economically significant returns. Positive but insignificant returns after 1995 seemed to be related with a decrease in central bank intervention activities. Transaction costs did not affect technical trading returns except for a few short-term trading rules. Over the 1980-98 period, annualized Sharpe ratios for a 150-day trading rule and investing in the S&P500 were 0.65 and 0.49, respectively. However, a preliminary analysis using an international CAPM indicated that the hypothesis that there was a time-varying risk premium in the technical trading returns correlated with central bank interventions could not be rejected.

Table 5 Summary of genetic programming technical analysis studies published between 1988 and 2004

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
1. Neely, Weller, & Dittmar (1997)	6 exchange rates: mark, yen, pound, Swiss franc, and two cross rates (mark/yen and pound/Swiss franc) / Daily	1975-77, 1978-80, (1981-95)	100 trading rules generated by genetic programming during each in-sample period	Buy & hold / Optimized trading rules	In-sample periods: 0.1% per round-trip; out-of-sample period: 0.05%	Out-of-sample, genetic trading rules generated positive mean excess returns after transaction costs for every currency tested. The mean excess return across all currencies was 2.9% per year, being higher than the B&H return (0.6%). Since betas for these trading rule returns against various world market indices were negative, the excess returns did not seem to be compensation for bearing systematic risk. In addition, the superior performance of trading rules could not be explained by standard statistical models such as a random walk, ARMA, and ARMA-GARCH.
2. Allen & Karjalainen (1999)	S&P 500 Index / Daily	1929-82 (1936-95)	100 trading rules generated by genetic programming during each in-sample period	Buy & hold	One-way transaction costs of 0.1, 0.25, and 0.5%	After considering reasonable one-way transaction costs of 0.25%, average excess returns of optimal trading rules were negative for 9 of 10 out-of-sample periods. Even after transaction costs of 0.1%, average excess returns were negative for 6 out of the 10 periods. In most periods, only a few trading rules indicated positive excess returns. Overall, genetically formulated trading rules did not generate excess returns over the B&H strategy after transaction costs.
3. Fyfe, Marney, & Tarbert (1999)	U.K. Land Securities / Daily	1980-82, 1982-84 (1985-97)	The fittest trading rule generated by genetic programming during an in-sample period	Buy & hold / Optimized trading rules	1% per one-way transaction	Although an optimal trading rule performed well during the out-of-sample period, it appeared to have a similar structure to the B&H strategy. When the optimal trading rule was applied to price series bootstrapped by three popular statistical models (a random walk, AR (1), AR (1)–ARCH (3)), only the AR (1) model explained about 40% of the original excess trading returns.
4. Neely & Weller (1999)	4 cross exchange rates (mark/franc, mark/lira, mark/guilder, mark/pound) / Daily	1979-86 (1986-96)	100 trading rules generated by genetic programming, moving average (1/10, 1/50, 5/10, and 5/50 days), and filter (0.5, 1, 1.5, and 2%)	Buy & hold / Optimized trading rules	In-sample periods: 0.1% per round-trip; Out-of-sample period: 0.05%	During the out-of-sample period, annual mean excess returns averaged across 100 rules after transaction costs were positive for all four currencies, ranging 0.1% for the mark/guilder to 2.8% for the mark/pound. In contrast, moving average rules and filter rules generated annual mean excess returns of -0.1% and -0.2% across all currencies, respectively. There was no evidence that the excess returns to genetic trading rules were compensation for bearing systematic risk.

Table 5 continued.

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
5. Wang (2000)	S&P Index and S&P Index Futures / Daily	1984-97 (1987-98)	10 trading rules generated by genetic programming during each in-sample period	Buy & hold / Optimized trading rules	$0.50 per share + $25 per one-way transaction for spot index; $61 per round-trip for futures	For S&P futures, 36 out of 120 trading rules over the entire sample period outperformed the B&H strategy in terms of net returns. However, the results varied from year-to-year. Similar results were found when both S&P spot and futures markets were simultaneously considered for trading. When risk-adjusted returns were assessed, 57 out of 120 rules beat the B&H strategy. Although the performance of trading rules was still inconsistent over sample periods, more than 40% of the rules appeared to have some market-timing capability.
6. Neely & Weller (2001)	4 foreign exchange rates: mark, yen, pound, and Swiss franc / Daily	1975-80 (1981-92), 1987-92 (1993-98)	100 trading rules generated by genetic programming during each in-sample period	Buy & hold / Optimized trading rules	In-sample periods: 0.1% per round-trip; out-of-sample period : 0.05%	Over the period 1981-92, intervention information from the Fed substantially improved the profitability of optimal trading rules for pound and Swiss franc. For example, the median portfolio rule increased annual excess returns from 0.5% to 7.2% per year for the pound. In contrast, over the 1993-98 period, intervention information decreased the profitability of trading rules for all currencies but the mark. Thus, intervention activity did not seem to be a general source of profits for technical traders.
7. Korczak & Roger (2002)	24 stocks of the CAC40 Index of the Paris Stock Exchange / Daily	Ten 261-day periods over 1/97-11/99 (Ten 7-day periods)	Trading rules generated by genetic programming during each in-sample period	Two buy & hold strategies /Optimized trading rules	0.25% per one-way transaction	Out-of-sample results indicated that genetic trading rules outperformed both B&H strategies in 9 out of 10 cases. Although newly generated trading rules performed well over time and relative to the old rules, all rules showed good and stable performance over the out-of-sample periods. No trading rule consistently performed better than others.
8. Ready (2002)	Dow Jones Industrial Average (DJIA) / Daily	1939-2000, 1957-62 (1963-86), 1981-86 (1987-00)	50 genetic-programming-based trading rules and 4 moving average rules from Brock et al. (1992)	Buy & hold, Stock/bond weighted average / Optimized trading rules	0.13% per one-way transaction	Moving average rules generated positive excess returns after transaction costs for the period 1963-86, although they yielded negative excess returns for the period 1987-2000. However, because moving average rules performed poorly from 1939-62, they were less likely to be chosen by traders at the beginning of 1963. In fact, every genetic trading rule created over the period 1957-60 outperformed the moving average rules. Similar results were found for the period 1987-2000. Hence, Ready concluded that Brock et al.'s (1992) results for the period 1963-86 were spurious.

Table 5 continued.

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
9. Neely (2003)	S&P 500 Index / Daily	1929-80 (1936-95)	10 trading rules generated by genetic programming during each in-sample period	Buy & hold / Optimized trading rules	0.25% per one-way transaction	During in-sample periods, genetic trading rules generated an about 5% annual mean excess return over the B&H strategy. During out-of-sample periods, however, genetic trading rules generated negative mean excess returns over the B&H strategy. The risk-adjusted performance based on several risk-adjusted return measures was inferior to that of the B&H strategy. In addition, trading rules optimized by various risk-adjusted criteria also failed to outperform the B&H strategy.
10. Neely & Weller (2003)	4 foreign exchange rates: mark, yen, pound, and Swiss franc / Intra-daily	2/96-5/96 (6/96-12/96)	25 trading rules generated by genetic programming for each currency;	An linear forecasting model / Optimized trading rules	0, 0.01, 0.02 and 0.025% per one-way transaction	There was strong evidence of predictability in exchange rate series tested because genetically trained trading rules yielded annual returns of over 100% with zero transaction costs in 3 of the 4 cases. However, under realistic trading hours and transaction costs (0.025%), genetic trading rules realized break-even transaction costs of less than 0.02% per one-way trade in all the exchange rates but the pound. Moreover, genetic trading rules appeared to be inferior to the autoregressive linear forecasting model in most cases, although their performances were not much different.
11. Roberts (2003)	CBOT corn, soybean, and wheat futures / Daily	1978-1998 (1980-1998)	The best of ten rules optimized during each in-sample period using genetic programming	Zero profits and buy & hold	\$25 and \$6.25 per contract per round-trip for in- and out-of-sample periods, respectively	Although genetically trained rules produced positive mean net returns only for wheat futures in out-of-sample tests, only trading rules that use the ratio of profit to maximum drawdown as a performance measure generated a statistically significant mean daily net profit of \$0.93 per contract. This was compared to the B&H profit of -\$3.30 per contract. For corn and soybean futures, however, genetic trading rules produced both negative mean returns and negative ratios of profit to maximum drawdown during the sample period.

Table 6 Summary of Reality Check technical analysis studies published between 1988 and 2004

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
1. Sullivan, Timmermann, & White (1999)	Dow Jones Industrial Average (DJIA), S&P 500 index futures / Daily	DJIA: 1897-1996, 1897-1986 (1987-96); S&P 500 futures: 1984-96	Filter, moving average, support and resistance, channel breakout, on-balance volume average	Zero mean profits for mean return, a risk-free rate for the Sharpe ratio / Optimized trading rules	Not adjusted	During the 1897-96 period, the best rule in terms of mean return was a 5-day moving average that produced an annual mean return of 17.2% with a data snooping adjusted p-value of zero. The corresponding break-even transaction cost was 0.27% per trade. The best rule in terms of the Sharpe ratio generated a value of 0.82 with a Bootstrap Reality Check p-value of zero, while the B&H strategy generated a Sharpe ratio of 0.034. However, during the 1987-96 period, the 5-day moving average rule earned a mean return of 2.8% per year with a nominal p-value of 0.32. Moreover, in the S&P 500 futures market, the best rule generated a mean return of 9.4% per year with a Bootstrap Reality Check p-value of 0.90, implying that the return resulted from data snooping.
2. Qi & Wu (2002)	7 foreign exchange rates: mark, yen, pound, lira, French franc, Swiss franc, and Canadian dollar / Daily	1973-1998	Filter, moving average, support and resistance, and channel breakout	Buy & hold, Zero mean profits /	Adjusted	During the sample period, the best trading rules, which are mostly moving average rules and channel breakout rules, produced positive mean excess returns over the buy-and-hold benchmark across all currencies and had significant data snooping adjusted p-values for the Canadian dollar, the Italian lira, the French franc, the British pound, and the Japanese yen. The mean excess returns were economically substantial (7.2% to 12.2%) for all the five currencies except for the Canadian dollar (3.6%), even after adjustment for transaction costs of 0.04% per one-way transaction. In addition, the excess returns could not be explained by systematic risk. Similar results were found for the Sharp ratio criterion, and the overall results appeared robust to incorporating transaction costs into the general trading model, changes in a vehicle currency, and changes in the smoothing parameter in the stationary bootstrap procedure.
3. Sullivan, Timmermann, & White (2003)	Dow Jones Industrial Average (DJIA), S&P 500 index futures / Daily	DJIA: 1897-1998, 1987-96; S&P 500 futures: 1984-96	Technical trading systems from Sullivan et al. (1999) and calendar frequency trading rules from Sullivan et al. (2001)	Buy & hold / Optimized trading rules	Not adjusted	For the full sample period (1897-1998), the best of the combined universe of trading rules, a 2-day-on-balance volume strategy, generated a mean return of 17.1% on DJIA data with a data snooping adjusted p-value of zero, and outperformed the B&H strategy (a mean return of 4.8%). For a recent period (1987-96), the best rule, a week-of-the-month strategy, produced a mean return of 17.3% slightly higher than the B&H return (13.6%), but the return was not statistically significant (p-value of 0.98). Similar results were found for the S&P 500 futures data. Although the best rule (a mean return of 10.7%) outperformed the benchmark (mean return of 8.0%) during the 1984-96 period, the data snooping adjusted p-value was 0.99.

Table 7 Summary of chart pattern studies published between 1988 and 2004

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
1. Curcio, Goodhart, Guillaume, & Payne (1997)	3 foreign currencies: mark, yen, and pound / Intradaily (one hour frequency)	4/89-6/89, 1/94-6/94	Support and resistance, high-low, minimum of the support and low and maximum of the resistance and high, and max-min	Buy & hold	Bid-ask spreads	Across exchange rates tested, the results of the earlier sample period indicated that only 4 of 36 buy and sell rules yielded statistically significant positive returns after transaction costs. Max-min rules showed even worse performance. For the later period, 10 rules had positive returns but 14 rules produced significantly negative returns. Max-min rules all realized negative returns.
2. Caginalp & Laurent (1998)	All world equity closed end funds listed in Barron's and all S&P 500 stocks / Daily	4/92-6/96, 1/92-6/96	Candlestick patterns	Average return	Commissions ($20 for several thousand shares) and the bid-ask spread (0.1-0.3%)	Candlestick reversal patterns appeared to have statistically significant short-term predictive power for price movements. Each of the patterns generated substantial profits in comparison to an average gain for the same holding period. For the S&P 500 stocks, down-to-up reversal patterns produced an average return of 0.9% during a two-day holding period (annually 309% of the initial investment). The profit per trade ranged from 0.56%-0.76% even after adjustment for commissions and bid-ask spreads on a $100,000 trade, so that the initial investment was compounded into 202%-259% annually.
3. Chang & Osler (1999)	6 spot currencies: yen, mark, pound, Canadian dollar, Swiss franc, and French franc / Daily	1973-94	Head-and-shoulders, moving average (1/5, 1/20, 5/20, 5/50, and 20/50 days), and momentum (5-, 20-, and 50-day lags)	Buy & hold, Equity yields	0.05% per round-trip	Head-and-shoulders rules earned substantial returns for the mark and yen but not for other currencies. Profits for the mark and yen were around 13% and 19% per year, respectively, with being higher than the corresponding B&H returns or U.S. equity yields. These results were evident even after adjusting for transaction costs, risk, or interest differentials. However, moving average rules and momentum rules appeared to have significant predictive power for all six currencies. Moreover, they easily outperformed head-and-shoulders rules in terms of total profits and Sharpe ratios.
4. Guillaume (2000)	3 exchange rates: mark/dollar, yen/dollar, dollar/pound / Intra-daily	4/89-6/89, 1/94-6/94	4 trading range breakouts with a 0.1% band	Buy & hold	Bid-ask spreads	For the first sample period, several trading rules generated statistically significant net profits, particularly, in trending markets such as the yen/dollar market. For the second period, however, none of the trading rules produced significant net profits, even in trending markets. In general, support-resistance rules performed better than Max-Min rules used in Brock et al. (1992).

Table 7 continued.

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
5. Lo, Mamaysky, & Wang (2000)	Individual NYSE/AMEX and Nasdaq stocks / Daily	1962-96	Head-and-shoulders (H&S)and inverse H&S, broadening tops and bottoms (T&B), triangle T&B, rectangle T&B, and double T&B	Not considered	Not adjusted	Pattern-recognition algorithms were used to detect 10 chart patterns in price series smoothed by using non-parametric kernel regressions. The results of goodness-of-fit and Kolmogorov-Smirnov tests indicated that, in many cases, return distributions conditioned on technical patterns were significantly different from unconditional return distributions, especially, for the Nasdaq stocks. This suggests that technical patterns may provide some incremental information for stock investment, even if they may not be used to generate excess trading profits.
6. Osler (2000)	3 foreign exchange rates: mark, yen, and pound against U.S. dollar / Intra-daily	1/96-3/98	Support and resistance	Not considered	Not adjusted	“Bounce frequency” of support and resistance levels for each currency published by six firms was compared to that of artificial support and resistance levels. Results indicated that trends in intra-daily exchange rates were interrupted at the published support and resistance levels more frequently than at the artificial ones. The results were consistent across all three exchange rates and all six firms, although the predictive power of the published support and resistance levels varied. Moreover, the results were statistically significant and robust to alternative parameterizations.
7. Leigh, Paz, & Purvis (2002)	The NYSE Composite Index / Daily	1980-99	Bull flag charting patterns	Buy & hold	Not adjusted	Across all parameter combinations considered, trading rule returns in excess of the B&H strategy were positive for all forecasting horizons (10, 20, 40, and 80 days). Moreover, results of linear regression analyses indicated that trading rule parameters had predictive value for both price level and future price direction.
8. Leigh, Modani, Purvis, & Roberts (2002)	The NYSE Composite Index / Daily	1980-99 (the first 500 trading days)	Two bull flag patterns with trading volume (a buy position is held for 100 days)	Buy & hold / Optimized parameters	Not adjusted	During the out-of-sample period, patterns outperformed the B&H strategy. The first and the second bull flag patterns with trading volume generated statistically significant mean returns of 14.0% (with 55 buy signals) and 8.6% (with 132 buy signals) for 100-day holding period, respectively, while the B&H strategy profited 5.5%.
9. Dawson & Steeley (2003)	225 individual FTSE100 and FTSE250 stocks / Daily	1986-2001	The same patterns as in Lo et al. (2000)	Buy & hold	Not adjusted	This study replicates Lo et al.’s (2000) procedure on UK data. Results were similar to Lo et al.’s finding. The results of goodness-of-fit and Kolmogorov-Smirnov tests indicated that return distributions conditioned on technical patterns were significantly different from the corresponding unconditional distributions. However, across all technical patterns and sample periods, an average market adjusted return turned out to be negative.

Table 7 continued.

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
10. Lucke (2003)	Dollar, mark, pound, yen, and Swiss franc / Daily	1973-99	Head-and-shoulders	Not considered	Not adjusted	In general, head-and-shoulders rules failed to generate positive mean returns for all holding periods (1 to 15 days) except a one-day holding period. In addition, it appeared that trading rule profits were not correlated with central bank intervention.
11. Zhou & Dong (2004)	1451 stocks listed on the NYSE, Amex, NASDAQ / Daily	1962-2000	Head-and-shoulders (HS)and inverse HS (HIS), broadening tops (BT) and bottoms (BB), triangle tops (TT) and bottoms (TB), rectangle tops (RT) and bottoms (RB)	Returns for a size- and momentum-matched control company	Not adjusted	To reflect the uncertainty of human perception and reasoning, fuzzy logic were incorporated into the definition of well-known technical patterns. For all stocks tested, the HS, HIS, RT, and RB patterns generated significant cumulative abnormal returns (CARs) of around 3% for 120 days. For stocks trading above $2.00, however, the significance of CARs dramatically reduced or disappeared. The effect of small trading prices was more severe for NASDAQ stocks. For the HS, IHS, and RB patterns, the fuzzy logic-based algorithm appeared to detect subtly different post-pattern performances between two portfolios with different pattern membership values. The results for four subperiods indicated that for the RT pattern the post-pattern performances of two portfolios with different membership values were significantly different in the first three subperiods from 1962 through 1990. This may imply that stock markets have been efficient after the early 1990s.

Table 8 Summary of nonlinear technical analysis studies published between 1988 and 2004

Study (Criteria:)	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
1. Gençay (1998a)	Dow Jones Industrial Average (DJIA) / Daily	1963-88 (Last 250 prices for each of 6 sub-samples)	Trading rules based on a feedforwad network model	Buy & hold / Optimized models	$600 per round-trip for the contract value of 1,000,000	Trading signals as a function of past returns were generated by a feedforward network, which is a class of artificial neural networks. Across subperiods, net returns of technical trading rule (7% to 35%) dominated those of the B&H strategy (-20% to 17%). Sharpe ratio tests indicated similar results. Correct sign predictions for the recommended positions ranged from 57% to 61% for all subperiods.
2. Gençay (1998b)	Dow Jones Industrial Average (DJIA) / Daily	1897-1988 (10 most recent prices for each of 22 sub-samples)	Trading rules based on a feedforwad network model	An OLS model with lagged returns as regressors / Optimized models	Not adjusted	In terms of forecast improvement measured by the mean square prediction error (MSPE), non-linear models (feedforward network models) using past buy-sell signals from moving average rules (1/50 and 1/200) as regressors outperformed linear specifications such as the OLS, GARCH-M (1,1), and a feedforward network regression with past returns. For 14 of 22 subperiods, the nonlinear models generated at least 10% forecast improvement over the benchmark model. The model with a 1/50 moving average rule provided more accurate out-of-sample predictions relative to one with a 1/200 rule.
3. Gençay & Stengos (1998)	Dow Jones Industrial Average (DJIA) / Daily	1963-88 (Last 1/3 of the data set for each of 6 sub-samples)	Trading rules based on a feedforwad network model	An OLS model with lagged returns as regressors / Optimized models	Not adjusted	Overall non-linear models (feedforward network models) outperformed linear models (OLS and GARCH-M (1,1)) in terms of MSPEs and sign predictions. The non-linear models with lagged returns generated an average of 2.5% forecast improvement over the benchmark model with lagged returns. This prediction power improved as large as 9.0% for the non-linear models in which past buy-sell signals of a moving average rule (1/200) were used as regressors. In particular, when the non-linear model included a 10-day volume average indicator as an additional regressor, it produced an average of 12% forecast gain over the beanchmark and provided much higher correct sign predictions (an average of 62%) than other models.
4. Gençay (1999)	5 spot exchange rates: pound, mark, yen, France franc, and Swiss franc / Daily	1973-92 (Last 1/3 of the data set)	Trading rules based on a feedforwad network model and the nearest neighbor regression	Random walk and GARCH (1,1) models / Optimized models	Not adjusted	Nonlinear models such as the nearest neighbors and the feedforward network regressions with past buy-sell signals from moving average rules (1/50 and 1/200) outperformed a random walk and a GARCH (1,1) model in terms of sign predictions and mean square prediction errors. For example, average correct sign prediction of the nearest neighbors model was 62% for the five currencies. Models with a 1/50 moving average rule provided more accurate predictions over models with a 1/200 rule.

Table 8 continued.

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
5. Fernández-Rodríguez, González-Martel, & Sosvilla-Rivero (2000)	The General Index of the Madrid Stock Market / Daily	1966-97 (10/91-10/92, 7/94-7/95, 10/96-10/97)	A trading rule based on a feedforwad network model	Buy & hold	Not adjusted	In terms of gross returns, a trading rule based on a feedforwad network model dominated the B&H strategy for two subperiods, while the opposite was true for most recent subperiods in which there exists upwards trend. Correct sign predictions for the recommended positions ranged from 54-58%, indicating better performance than a random walk forecast.
6. Sosvilla-Rivero, Andrada-Félix, & Fernández-Rodríguez (2002)	Mark and yen / Daily	1982-96	A trading rule based on the nearest neighbor regression	Buy & hold / Optimized models	0.05% per round-trip	Trading rule generated net returns of 35% and 28% for the mark and yen, respectively, and outperformed B&H strategies that yielded net returns of -1.4% and -0.4%, respectively. Correct sign predictions for recommended positions were 53% and 52% for the mark and yen, respectively, beating a random walk directional forecast. However, when excluding days of US intervention, net returns from the trading strategy substantially decreased (-10% and -28% for the mark and yen, respectively) and were less than the B&H returns in both cases.
7. Fernández-Rodríguez, Sosvilla-Rivero, & Andrada-Félix (2003)	9 exchange rates in the European Monetary System (EMS) / Daily	1978-94,	Trading rules based on the nearest neighbor (NN) and the simultaneous NN regressions and moving averages (1/50, 1/150, 1/200, 5/50, and 5/200 days)	Not considered / Optimized models	0.05% per round-trip	For most exchange rates, annual mean returns from nonlinear trading rules based on the nearest neighbor or the simultaneous nearest neighbor regressions were superior to those of moving average rules. The nonlinear trading rules also generated statistically significant annual net returns of 1.5%-20.1% for the Danish krona, French franc, Dutch guilder, and Italian lira. Similar results were found for the Sharp ratio criterion. The nonlinear trading strategies generated the highest Sharpe ratios in 8 out of the 9 cases.

Table 9 Summary of other technical analysis studies published between 1988 and 2004

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
1. Pruitt & White (1988)	204 stocks from the CRSP at the University of Chicago / Daily	1976-85	CRISMA (combination system of **C**umulative volume, **R**elat**I**ve **S**trength, and **M**oving **A**verage)	Buy & hold	0 to 2% per round-trip	After 2% transaction costs and across various return-generating models, the CRISMA system yielded annual excess returns ranging from 6.1% to 15.1% and beat the B&H or market index strategy. The system also generated a much greater percentage of profitable trading successes after transaction costs than would be expected by chance.
2. Schulmeister (1988)	Mark / Daily	1973-88	Moving average, momentum, point & figure, combination of moving average & momentum	Buy & hold	0.04% per one-way transaction	All trading rules considered produced substantial annual returns up to 16%. The combination system performed best. The probability of an overall loss appeared to be less than 0.005% when one of the trading rules was followed blindly during the 1973-86 period.
3. Sweeney (1988)	14 Dow-Jones Industrial stocks / Daily	1956-62 (1970-82)	0.5% filter rule	Buy & hold	From 0.05% to 0.2% per one-way transaction	During the 1970-82 period, for 11 of 14 stocks that had earned profits before commissions in Fama and Blume's (1966) study, a 0.5% filter rule produced statistically significant annual mean returns after adjustment for transaction costs of 0.1%. For an equally weighted portfolio of 14 stocks, the filter rule generated a mean net return of 10.3% per year. Portfolio returns appeared to be robust across several subsamples but were quite sensitive to transaction costs.
4. Taylor (1988)	Treasury bond futures from CBOT / Daily	1978-87	A statistical price-trend model based on ARMA(1,1)	Buy & hold	0.2% per round-trip	All four trading rules generated positive average excess returns ranging from 4.4% to 6.8% per year and were superior to the B&H strategy. However, t-test results indicated that none of the returns was significantly different from zero at the 5% level. In addition, the B&H strategy performed better than each trading rule from 1982-87.
5. Pruitt & White (1989)	In-the-money call options written on the 171 stocks / Daily	1976-85	CRISMA	Not considered	Maximum 1988 retail transaction costs	After transaction costs, the CRISMA system generated a mean return of 12.1% per round trip. In fact, 71.3% of the 171 transactions were profitable after adjustment for transaction costs. The binomial proportionality test statistics showed that the trading profitability could not be achieved by chance.
6. Neftci (1991)	Dow-Jones Industrials / Monthly	1792-1976	Moving average (150 days)	Not considered	Not adjusted	This study showed that moving average rules were one of the few statistically well-defined procedures. Trading signals of a 150-day moving average rule were incorporated into a dummy variable in an autoregression equation. F-test results on the variable were insignificant for 1795-1910 but highly significant for 1911-76, indicating some predictive power of the moving average rule.

Table 9 continued.

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
7. Corrado & Lee (1992)	120 stocks from the Dow Jones and S&P 500 Index / Daily	1963-89	0.5% own-stock filter, 0.25% S&P 500 Index filter, 0.5% other-stock filter	Buy& hold	0.04% per one-way transaction	The own-stock filter rule generated an equally-weighted mean portfolio return of 30.8% per year during the sample period, while the B&H strategy yielded a mean portfolio return of 11.3% per year. This difference between the returns made an annual gross margin of 6.4% over the B&H strategy after transaction costs.
8. Pruitt, Tse, & White (1992)	148 stocks and in-the-money call options written on the 126 target stocks / Daily	1986-90	CRISMA (combination system of **C**umulative volume, **R**elat**I**ve **S**trength, and **M**oving **A**verage)	Buy& hold	Security: 0-2% per round-trip; Option: $60 per round-trip	For stocks, the CRISMA system generated annualized excess returns of between 1.0% and 5.2% after transaction costs of 2% and outperformed the B&H or market index strategy. For options, the system generated highly significant returns of 11.0% per option trade after transaction costs, with 63.5% of all trades being profitable.
9. Wong (1995)	Hang Seng Index (HSI) / Daily	1969-1990, 5 subperiods	Moving average (10, 20, and 50 days)	Buy & hold	Not adjusted	In general, moving average rules performed well. In particular, an MA10 (a 10-day moving average) bullish signal, an MA20 bullish signal, and an MA50 bearish signal generated statistically significant excess returns over the B&H strategy. It appeared that for buy (sell) signals, prices declines (rises) slowly in the early pre-event period and rises (declines) sharply in the late pre-event period. Prices continued to rise (declines) slowly in the post-event period for buy (sell) signals.
10. Cheung & Wong (1997)	Yen, Singapore dollar, Malaysian ringgit, and Taiwan dollar / Daily	1986-95	Filter (0.5, 1, and 1.5%)	Buy & hold	1/8 of 1% of asset value per round-trip	When transaction costs and risk were adjusted, filter rules generated superior excess returns over the B&H strategy only for the Taiwan dollar. Filter rules were inferior to the B&H strategy in the cases of the yen and Singapore dollar. Both filter rule and B&H strategies failed to generate significant excess returns on the Malaysian ringgit.
11. Irwin, Zulauf, Gerlow, & Tinker (1997)	Futures contracts for soybean, soybean meal, and soybean oil / Daily and monthly	1974-83 (1984-88)	Channel (40 days), ARIMA(2,0,0) for soybean and ARIMA(1,0,1) for soybean mean and oil	Zero mean profits	Not adjusted	During the out-of-sample period, the channel system generated statistically significant mean returns ranging 5.1%-26.6% for all markets. The ARIMA models also produced statistically significantly positive returns (16.5%) for soybean meal, but significantly negative returns (-13.5%) for soybeans. For every market, the channel system beat the ARIMA models.

Table 9 continued.

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
12. Neely (1997)	4 foreign currencies: mark, yen, pound, and Swiss franc / Daily	1974-97	Filter (0.5, 1, 1.5, 2, 2.5, and 3%) and moving average (1/10, 1/50, 5/10, and 5/50 days)	Buy & hold the S&P 500 index	0.05% per round-trip	Technical trading rules showed positive net returns in 38 of the 40 cases. In general, moving average rules performed slightly better than filter rules. Moreover, the trading profits were not likely to be compensation for bearing risk. For example, for the mark, every moving average rule beat the B&H strategy of the S&P 500 Index in terms of the Sharpe ratio. The CAPM betas from the trading rules also generally indicated negative correlation with the S&P 500 monthly returns.
13. Goldbaum (1999)	U.S. T-Bills, a value-weighted market portfolio of all the NYSE and AMEX securities from the CRSP, and IBM stock / Daily	1962-89	Moving average (1/50, 1/200, 5/50, and 5/200 days with 0 and 1% bands)	T-Bill returns	Not adjusted	As a performance measure, the price error between assets was estimated using the nonparametric stochastic discount factor (SDF), which was either conditioned or unconditioned on public information (e.g. term structure). For the market portfolio returns, moving average rules generally had unconditional estimates that were significantly positive or close to zero and conditional estimates that were negative or close to zero, implying a negative performance of the trading rules to an informed trader. For IBM stock returns, however, the conditional estimates on the term structure were significantly different from zero.
14. Marsh (2000)	3 IMM currency futures: mark, yen, and pound sterling / Daily	1980-96, 1980-85 (1986-90), 1980-90 (1991-95)	Markov models and moving average rules (1/5, 5/20, and 1/200 days)	Not considered	0.025% and 0.04% per one-way transaction	Before transaction costs, all moving average rules tested yielded positive returns for both 1981-85 and 1986-90, but the rules generated positive returns only in 3 out of 9 cases for 1991-95. For out-of-sample periods, Markov models also generated positive returns in 2 out of 6 cases. Augmented Markov models, in which interest differentials were included, produced substantially positive returns for all 3 currency futures during 1986-90 but only for the yen during 1991-95.
15. Dewachter (2001)	4 foreign exchange rates: mark, yen, pound, and franc / Weekly	1973-97	Moving average (1/30) with a 5-day holding period, Markov model and its ARMA (1,1) representation as the class of Taylor's price-trend models	Not considered	Not adjusted	Across exchange rates, the moving average rule produced a statistically significant average return of about 6% per year and the correct sign prediction of about 55%. The extended Markov switching model and the ARMA (1,1) representation of the Markov switching model showed even better performance in terms of profits and sign prediction. The results of Monte Carlo simulations indicated that the Markov model could replicate the observed profitability of the moving average rule.
16. Wong, Manzur, & Chew (2003)	Singapore Straits Times Industrial Index (STII) / Daily	1974-1994, Three 7-year subperiods	Moving averages and relative strength index (RSI)	Not considered	Not adjusted	In general, every trading system tested produced statistically significant returns over all three subperiods and a whole period. Single moving average rules generated the best results, followed by dual moving average crossover rules and relative strength index rules.

Table 10 The profitability of technical trading strategies in modern studies (1988-2004)

Studies	The number of studies			Net profit range (Out-of-sample period)	Comments
	Positive	Mixed	Negative		
A. Stock markets					• For the Dow Jones Industrial Average (DJIA) data, which was most frequently tested in the literature, results varied considerably depending on the testing procedure adopted. In general, technical trading strategies were profitable until the late 1980s. However, technical trading strategies were no longer economically profitable thereafter. • Overall, variable-moving average rules showed a quite reliable performance for the stock market over time. • For several non-US stock markets (e.g., Mexico, Taiwan, and Thailand), moving average rules generated large annual net profits of 10% to 30% until the mid-1990s.
Standard	1	0	3	1.1%[a] (1968-88)	
Model-based Bootstrap	7	2	3		
Genetic programming	2	1	3		
Reality Check	0	1	1		
Chart patterns	5	0	1		
Nonlinear	3	0	1		
Others	8	1	0		
Sub-total	24	5	12		
B. Currency markets					• Many studies investigated major foreign currency futures contracts traded on the CME, i.e., the Deutsche mark, Japanese yen, British pound, and Swiss franc. • For major currencies, a wide variety of technical trading strategies, such as moving average, channel, filter, and genetically formulated trading rules, consistently generated economic profits until the early 1990s. • Several recent studies confirmed the result, but also reported that technical trading profits have declined or disappeared since the early 1990s, except for the yen market.
Standard	7	3	3	5%-10% (1976-91)	
Model-based bootstrap	6	0	1		
Genetic programming	3	0	1		
Reality Check	1	0	0		
Chart patterns	2	0	3		
Nonlinear	3	0	0		
Others	3	1	1		
Sub-total	25	4	9		
C. Futures markets					• Technical trading strategies generated economic profits in futures markets from the late 1970s through the mid-1980s. In particular, technical trading strategies were consistently profitable in most currency futures markets, while they appeared to be unprofitable in livestock futures markets. • Channel rules and moving average rules were the most consistent profitable strategies. • After the mid-1980s, the profitability of technical trading strategies for overall futures markets were not investigated comprehensively yet.
Standard	5	0	1	4%-6% (1976-86)	
Model-based bootstrap	1	0	1		
Genetic programming	0	1	0		
Others	1	0	1		
Sub-total	7	1	3		
Total	58	10	24		

[a] This is a break-even one-way transaction cost of a 5/200 moving average rule, which was optimized by using the DJIA data from 1897 to 1968 (Taylor 2000).