What Do We Know about the Profitability of Technical Analysis?*

by

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Abstract

The purpose of this article is to review the evidence on the profitability of technical analysis. The empirical literature is categorized into two groups, 'early' and 'modern' studies, according to the characteristics of testing procedures. Early studies indicate that technical trading strategies are profitable in foreign exchange markets and futures markets, but not in stock markets. Modern studies indicate that technical trading strategies consistently generate economic profits in a variety of speculative markets at least until the early 1990s. Among a total of 95 modern studies, 56 studies find positive results regarding technical trading strategies, 20 studies obtain negative results, and 19 studies indicate mixed results. Despite the positive evidence on the profitability of technical trading strategies, 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.

Key words: Market efficiency; Technical analysis; Speculative markets; Trading systems

What Do We Know about the Profitability of Technical Analysis?

1. Introduction

Technical analysis is a method of forecasting price movements using past prices, volume, and/or open interest.[1] Pring (2002, p. 2), 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.

Technical analysis includes a variety of forecasting techniques such as chart analysis, cycle analysis, and computerized technical trading systems. Academic research on technical analysis generally is limited to techniques that can be expressed in mathematical form, 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 generate trading signals (long, short, or out of the market) according to various parameter values. Popular technical trading systems include moving averages, channels, and momentum oscillators.

Technical analysis has a long history of widespread use by participants in speculative markets.[2] In pioneering work, Smidt (1965b) surveys amateur traders in U.S. commodity futures markets and finds that over half of the respondents use charts exclusively or moderately in order to identify trends.[3] More recently, Billingsley and Chance (1996) find that about 60% of commodity trading advisors (CTAs) rely heavily or exclusively on computer-guided technical trading systems. Fung and Hsieh (1997) estimate 'style' factors for CTAs and conclude that trend-following is the single dominant strategy. Finally, surveys show that 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 Chinn, 2001; Gehrig and Menkhoff, 2003).

In sharp contrast to the views of many practitioners, academics tend to be skeptical about technical analysis. The skepticism can be linked to: (1) acceptance of the efficient market hypothesis (Fama, 1970), which implies that it is futile to attempt to make profits by exploiting currently available information such as past price trends; and (2) negative empirical findings in several early and widely-cited studies of technical analysis in the stock market, such as Fama and Blume (1966), Van Horne and Parker (1967, 1968), and Jensen and Benington (1970).

The controversy about the usefulness of technical analysis has led to a voluminous literature on the subject. Empirical studies have investigated 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 concentrate on stock markets, both in and outside the U.S., and foreign exchange markets. A smaller number of studies analyze futures markets. Table 1 presents the number of technical trading studies over the last four decades. The explosion in the literature on technical analysis in recent years is especially noteworthy. About half of all empirical studies conducted after 1960 were published during 1995-2004. Such a huge increase may result from: (1) the publication of several seminal papers (e.g. Sweeney, 1986; Brock *et al*., 1992) between the mid-1980s and early 1990s, which in contrast to earlier studies found significant technical trading profits; and (2) the availability of cheaper computing power and the development of electronic databases of prices (for a complete annotated summary of all studies, see Park and Irwin, 2004).

Despite the explosion in the literature on technical analysis, no study has surveyed this literature systematically and comprehensively. The purpose of this article is to comprehensively review the empirical literature on technical analysis and discuss the consistency and reliability of evidence on technical trading profits across markets and over time. 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, treatment of transaction costs, risk, data snooping problems, parameter optimization, out-of-sample verification, and statistical tests adopted. Empirical studies surveyed include those that test technical trading systems, trading rules formulated by genetic algorithms or some statistical models (e.g. ARIMA), and chart patterns that can be represented algebraically. Special attention is paid to testing procedures used in empirical studies and identification of their salient features and weaknesses. This will improve understanding of the profitability of technical trading strategies and suggest directions for future research.

2. The Efficient Market Hypothesis

Before surveying the empirical literature on the profitability of technical trading, it is useful to briefly review the efficient market hypothesis, long the dominant paradigm in describing the behavior of prices in speculative markets.[4] Fama (1970, p. 383) provides the textbook definition of an efficient market: 'A market in which prices always 'fully reflect' available information is called *efficient*'. Jensen (1978, p. 96) developed a more detailed definition: '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.

Jensen also subdivided the efficient markets hypothesis into three types based on definitions of the information set q_t:

(1) Weak form efficiency, where the information set q_t is limited to the information contained in the past price history of the market as of time *t*.
(2) Semi-strong form efficiency, where the information set q_t is 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 the semi-strong form.)
(3) Strong-form efficiency, where the information set q_t is all public and private information available at time *t*. (This includes the past history of prices and all other public information, so weak- and semi-strong forms are simply restricted versions of the strong-form.)

Timmermann and Granger (2004, p. 25) extended Jensen's definition by specifying how the information variables in q_t are used to generate forecasts. In their definition, a market is efficient with respect to 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.[5]

A key implication of the efficient market hypothesis is that any attempt to make profits by exploiting currently available information is futile. The market price already reflects all that can be known from available information. Therefore, the expected return for technical trading rules based only on the public record of past prices is zero. This logic was stated in colorful terms by Samuelson (1965, p. 44):

> …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.

3. Empirical Studies

The earliest empirical study included in this review is Donchian (1960). Although the boundary between early and modern studies is blurred, Lukac *et al.*'s (1988) work is regarded here as the first modern study because it is among the first to substantially improve upon early studies in several important ways. This study considers 12 technical trading systems, conducts out-of-sample verification for optimized trading rules with a statistical significance test, and measures the performance of trading rules after adjusting for transaction costs and risk. Thus, early studies are assumed to commence with Donchian's study 1960 and include studies through 1987, while modern studies begin with Lukac *et al.*'s 1988 study and cover studies through August 2004.

3.1. *Early Studies (1960-1987)*

Early studies investigate several technical trading systems, including filters (Alexander, 1961, 1964; Fama and Blume, 1966; Sweeney, 1986), stop-loss orders (Houthakker, 1961; Gray and Nielsen, 1963), moving averages (Cootner, 1962; James, 1968; Van Horne and Parker, 1967, 1968; Dale and Workman, 1980), channels (Donchian, 1960; Irwin and Uhrig, 1984), momentum oscillators (Smidt, 1965a), and relative strength (Levy, 1967a, 1967b; Jensen and Benington, 1970).[6] Filter rules, first introduced by Alexander (1961), were the most popular trading system tested. A filter rule generates a buy (sell) signal when today's closing price rises (falls) by x% above (below) its most recent low (high). Thus, all price movements smaller than a specified filter size are 'filtered' and the remaining movements examined. In the best-known and most influential work on technical trading rules in the early period, Fama and Blume (1966) exhaustively test Alexander's filter rules on daily closing prices of 30 individual securities in the Dow Jones Industrial Average (DJIA) over 1956-1962. Across all 30 securities, only three small filter rules (0.5%, 1.0%, and 1.5%) generate higher annual mean returns on long positions than those of the buy-and-hold strategy. Fama and Blume conclude that excess profits on long transactions over the buy-and-hold strategy may be negative in practice if brokerage fees of specialists, the idle time of funds invested, operating expenses of the filter rules, and clearing house fees are taken into account. Other studies (e.g. Van Horne and Parker, 1967, 1968; James, 1968; Jensen and Benington, 1970) on stock markets also show that trading rules based on moving average or relative strength systems are not profitable.

In contrast, the majority of early technical trading studies on foreign exchange markets and futures markets find substantial net profits (e.g. Smidt, 1965a; Stevenson and Bear, 1970; Leuthold, 1972; Cornell and Dietrich, 1978; Dooley and Shafer, 1983; Irwin and Uhrig, 1984; Sweeney, 1986; Taylor, 1986). For example, Leuthold (1972) applies six filter rules to live cattle futures contracts over 1965-1970 and finds that four of them are profitable after transaction costs. In particular, a 3% filter rule generates an annual net return of 115.8% during the sample period. As another example, Sweeney (1986) investigates 10 foreign exchange rates using filter rules, showing that long positions based on small filters (0.5%, 1%, and 2%) generate positive risk-adjusted excess returns across all 10 exchange rates even after adjustment for transaction costs. Among the small filters, a 1% filter rule generates statistically significant risk-adjusted excess returns that average 3.0%-6.75% per year across exchange rates during 1975-1980.

These results suggest that stock markets were more efficient than foreign exchange markets or futures markets before the mid-1980s. This conclusion should be tempered in light of several limitations in the testing procedures of early studies. First, early studies generally consider a small number of trading systems, typically investigating only one or two trading systems. Thus, even if some studies demonstrate that technical trading rules do not generate significant profits, it may be premature to dismiss technical trading strategies.

Second, most early studies do not conduct statistical tests of significance on technical trading returns. Although several studies (James, 1968; Peterson and Leuthold, 1982; Bird, 1985; Sweeney, 1986) measure statistical significance using *Z*- or *t*-tests under the assumption that trading rule returns are normally distributed, applying such conventional statistical tests to trading rule returns is likely invalid since distribution of the returns under the null hypothesis of an efficient market is not known (Taylor, 1985). Furthermore, Lukac and Brorsen (1990) report that technical trading returns are positively skewed and leptokurtic and thus argue that past applications of *t*-tests to technical trading returns may be biased.

Third, the riskiness of technical trading rules is often ignored in early studies. If investors are risk-averse, they will consider the risk-return tradeoff of trading rules. Thus, large trading returns do not necessarily refute market efficiency since the returns may be compensation for taking greater risks. For the same reason, when comparing trading rule and benchmark returns, it is necessary to make explicit allowance for the difference of returns due to different degrees of risk. Only a few early studies (Jensen and Benington, 1970; Cornell and Dietrich, 1978; Sweeney, 1986) incorporate risk into testing procedures.

Fourth, the results of early studies are often difficult to interpret because the performance of trading rules is reported in terms of an 'average' across all trading rules or all assets (i.e., stocks, foreign exchanges, or futures contracts), rather than best-performing rules or individual securities. For example, Fama and Blume (1966) rely 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 for each individual stock, it is possible they may have reached different conclusions. Sweeney (1988, p. 296) points 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'.

Fifth, several authors speculate that substantial technical trading profits found in some early studies are attributable to data snooping (selection) biases. Since there is no structural form of a technical trading system that pre-specifies parameters, technical trading studies inevitably tend to search over a large number of parameters. When a large number of technical trading rules are searched, profitable trading rules may be identified by pure luck, and thus mislead researchers into believing that the rules have genuine predictive power. Jensen (1967, p. 81) recognizes this problem and argues 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?

Along the same lines, Jensen and Benington (1970, p. 470) state 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,…

Indeed, when typical technical trading rules such as filters and moving averages are applied to randomly generated price series, it turns out that the rules generate net profits for some of the random series by chance (Dooley and Shafer, 1983; Tomek and Querin, 1984).

To deal with data snooping problems, Jensen (1967) proposes a validation procedure where the best-performing trading model or models are identified in the first half of the sample period, and then are validated on the rest of the sample period. Optimizing trading rules is important because actual traders are likely to choose the best-performing rules in advance. Only Jensen and Benington (1970) follow an optimization and out-of-sample validation procedure, and moreover, only a few early studies (Irwin and Uhrig, 1984; Taylor, 1986) optimize trading rules.

3.2. *Modern Studies (1988-2004)*

As noted previously, the first 'modern' empirical study is assumed to be Lukac *et al*. (1988), who provide a more comprehensive analysis than any early study. Although modern studies generally have improved upon the limitations of early studies in terms of testing procedures, there are still considerable differences with regard to treatment of transaction costs, risk, parameter optimization, out-of-sample tests, statistical tests, and data snooping. Thus, modern studies are categorized into seven groups on the basis of differences in testing procedures. Table 2 provides general information about each group. 'Standard' refers to studies that include parameter optimization and out-of-sample tests, adjustment for transaction costs and risk, and statistical tests. 'Model-based bootstrap' represents studies that conduct statistical tests for trading returns using the model-based bootstrap approach introduced by Brock *et al*. (1992). 'Reality check' and 'genetic programming' indicate studies that attempt to solve data snooping problems using White's (2000) bootstrap reality check methodology and the genetic programming technique introduced by Koza (1992), respectively. 'Non-linear' indicates studies that apply non-linear methods such as feed-forward neural networks or nearest neighbor regressions to recognize patterns in prices or estimate the profitability of technical trading rules. 'Chart patterns' refers to studies that develop and apply recognition algorithms for chart patterns. Finally, 'other' refers to studies that do not fit neatly in any of the previous categories.

3.2.1. *Standard Studies*

In standard studies, technical trading rules are optimized based on a specific performance criterion and out-of-sample verification is implemented for the optimal trading rules. The parameter optimization and out-of-sample verification are significant improvements over early studies, in that these procedures are close to actual trader behavior and may partially address data snooping problems (Jensen, 1967; Taylor, 1986). Studies in this category incorporate transaction costs and risk into testing procedures and conduct conventional statistical tests of significance on trading returns.

Among standard studies, Lukac *et al.*'s (1988) work can be regarded as representative. Lukac *et al.* simulate 12 technical trading systems on price series from 12 agricultural, metal, and financial futures markets over 1975-1984. Technical trading is simulated using a three-year re-optimization method in which parameters generating the largest profit over the previous three years are used for the next year's trading, and at the end of the next year, new parameters are again optimized, and so on. This procedure assures that optimal parameters are adaptive and the simulation results are out-of-sample. Two-tailed *t*-tests are performed to test the null hypothesis that gross returns generated from technical trading are zero, while one-tailed *t*-tests are conducted to test the statistical significance of net returns after transaction costs. Based on the assumption that the capital asset pricing model (CAPM) holds, Jensen's α is used to determine the significance of risk-adjusted returns.

Lukac *et al.* find that four trading systems, including the dual moving average crossover and channel systems, yield statistically significant monthly portfolio net returns ranging from 1.89% to 2.78% after deducting transaction costs.[7] Deutsche mark, sugar, and corn appeared to be especially promising futures contracts since substantial net returns were observed across the various trading systems. Estimation results indicate that the same four trading systems have statistically significant Jensen's α intercepts, which implies that trading profits are not compensation for bearing systematic risk. Thus, Lukac *et al.* conclude that some futures markets are indeed inefficient during their sample period.

Lukac *et al.*'s (1988) testing procedure alleviates data snooping problems by considering a diverse set of technical trading systems and conducting parameter optimization and out-of-sample verification. However, their approach still has some limitations. First, the set of trading systems may not completely avoid data snooping biases if the selected systems reflect 'popular' systems known at the time of the study to have been profitable. Second, conventional *t*-tests may have reduced power if the return series are not normally distributed. Lukac and Brorsen (1990) find that individual market-level returns are in fact positively skewed and leptokurtic. However, portfolio returns for technical trading systems are normally distributed. Third, the CAPM may be an invalid pricing model for futures markets because the assumptions of the CAPM are inconsistent with the structure of futures markets (e.g. Stein, 1987).

Using similar procedures to those in Lukac *et al*. (1988), Lukac and Brorsen (1990) consider more trading systems and futures contracts and a longer sample period. They find that 7 out of 23 trading systems generate statistically significant positive net returns after adjustment for transaction costs. Among futures contracts tested, exchange rate futures earn the highest returns, while livestock futures have the lowest returns.

It is interesting to note that many studies in this category investigate foreign exchange markets. Technical trading rules not only yield unlevered annual net returns of 2%-10% for major foreign exchange futures contracts from the late 1970s to the early 1990s (Taylor and Tari, 1989; Taylor, 1992, 1994; Silber, 1994; Szakmary and Mathur, 1997), but also are profitable for some spot foreign exchange rates (Menkhoff and Schlumberger, 1995; Lee and Mathur, 1996a, 1996b; Maillet and Michel, 2000; Lee *et al*., 2001; Martin, 2001). However, profits of simple technical trading rules in foreign exchange markets seem to gradually decrease over time. Olson (2004) reports that risk-adjusted profits of moving average rules for a portfolio of 18 foreign exchange rates decline from over 3% in the late 1970s and early 1980s to near zero in the late 1990s. Taylor (2000) investigates a wide variety of U.S. and U.K. stock indices and individual stock prices, finding an average breakeven one-way transaction cost of 0.35% per transaction across all data series.[8] For the DJIA index, an optimal trading rule (a 5/200 moving average rule) estimated over 1897-1968 period produces a breakeven one-way transaction cost of 1.07% per transaction during 1968-1988.

3.2.2. *Model-Based Bootstrap Studies*

Model-based bootstrap studies apply a bootstrap methodology to test statistical significance of trading profits. Although some other recent studies of technical analysis use bootstrap procedures, model-based bootstrap studies differ from other studies in the sense that they typically analyze part or all of the trading rules (the moving average and the trading range break-out) that Brock *et al*. (1992) examined. The study by Brock *et al*. is one of the most influential works on technical trading rules among modern studies. The influence can be traced to the finding of strongly consistent and positive results about the forecasting power of technical trading rules, the use of a long price history (90 years for the Dow Jones Index), and application for the first time of the model-based bootstrap method.

Brock *et al*. (1992) apply the model-based bootstrap approach to overcome the weaknesses of conventional *t*-tests when financial returns have distributions known to be leptokurtic, autocorrelated, conditionally heteroskedastic, and time varying. In this approach, returns conditional on buy (or sell) signals from the original series are compared to conditional returns from simulated return series generated by widely used models for stock prices. The popular models adopted by Brock *et al*. include 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 is simulated by taking returns (logarithmic price changes) from the original series and then randomly re-sampling with replacement. For other models (AR (1), GARCH-M, EGARCH), parameters are first estimated using OLS or maximum likelihood and then residuals are randomly re-sampled with replacement. In this manner, 500 bootstrap samples of prices are generated for each null model and technical trading rules are applied to each of the 500 bootstrap samples. The empirical distribution for trading returns under each null model can be estimated based on these calculations. However, if the serial dependence of the actual return series is mis-specified in the null models or is highly complex, the model-based bootstrap method may provide inconsistent estimates (Maddala and Li, 1996; Ruiz and Pascual, 2002).

Brock *et al*. (1992) apply two technical trading systems, a moving average-oscillator and a trading range break-out (resistance and support levels), to the Dow Jones Industrial Average (DJIA) over 1897-1986. They recognize the potential for data snooping bias in technical trading studies and attempt to mitigate the problem by selecting technical trading rules that were popular over a long time period, reporting results from all trading strategies, utilizing a long data series, and emphasizing the robustness of results across various non-overlapping sub-periods.

Results indicate that buy (sell) signals from the technical trading rules generate positive (negative) returns across all 26 rules and 4 sub-periods tested. Thus, all the buy-sell differences are positive and outperform the buy-and-hold strategy. For example, buy (sell) returns are all positive (negative) for the variable-length moving average rules, with an annual return of 12% (-7%). As a result, all the buy-sell spreads are positive with an annual return of 19%, which compares favorably with a buy-and-hold return of 5%. Moreover, buy signals that generate higher average returns than sell signals have a lower standard deviation than sell signals. This implies that technical trading returns cannot be explained by risk. Hence, Brock *et al*. (1992, p. 1758) conclude 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'. Brock *et al*., however, report only gross returns of each trading rule without adjustment for transaction costs, so their results are not sufficient to prove that technical trading rules generate economic profits.

Bessembinder and Chan (1998) test the same trading rules as in Brock *et al*. (1992) on dividend-adjusted DJIA data over 1926-1991. Incorporating dividends tends to reduce returns on short sales and, in turn, may decrease technical trading returns (Fama and Blume, 1966). In an attempt to avoid data snooping problems, Bessembinder and Chan evaluate 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 difference across all rules is 4.4% per year (break-even one-way transaction costs of 0.39% per transaction) with a bootstrap *p*-value of zero. Non-synchronous trading with a one-day lag reduces the difference to 3.2% (break-even one-way transaction costs of 0.29% per transaction) with a significant bootstrap *p*-value of 0.002. However, break-even one-way transaction costs decline over time, and for the most recent sub-period (1976-1991), total 0.22% (without trade lag), less than estimated one-way transaction costs of 0.24%-0.26%. Thus, it is unlikely that traders could have used Brock *et al.*'s trading rules to earn net profits after transaction costs.

The results of the model-based bootstrap studies vary across markets and sample periods. In general, technical trading rules are profitable even after transaction costs for stock indices (spot or futures) in emerging markets (Bessembinder and Chan, 1995; Raj and Thurston, 1996; Ito, 1999; Ratner and Leal, 1999; Coutts and Cheung, 2000; Gunasekarage and Power, 2001), while profits for stock indices in developed markets are negligible after transaction costs or have declined over time (Hudson *et al.*, 1996; Mills, 1997; Bessembinder and Chan, 1998; Ito, 1999; Day and Wang, 2002). For example, Ratner and Leal (1999) document that Brock *et al.*'s moving average rules generate statistically significant net returns in four equity markets (Mexico, Taiwan, Thailand, and the Philippines) over the 1982-1995 period. Mills (1997) shows that mean daily returns from moving average rules applied to British equity markets are insignificantly different from a buy-and-hold return over 1975-1994. Returns are much higher than buy-and-hold returns for the 1935-1954 and 1955-1974 periods. Levich and Thomas (1993), LeBaron (1999), Neely (2002), and Saacke (2002) all report substantial profits of moving average rules in foreign exchange markets. For example, LeBaron (1999) finds that a 150-day moving average rule generates Sharpe ratios of 0.60-0.98 after transaction costs of 0.1% per round-trip in mark and yen markets during 1979-1992. The reported Sharpe ratios are much greater than those for buy-and-hold strategies on aggregate U.S. stock portfolios (0.3-0.4).

3.2.3. *Reality Check Studies*

Reality check studies use White's (2000) bootstrap reality check methodology to assess data snooping bias associated with an 'in-sample' search for profitable trading rules. White's statistical procedure can directly quantify the effect of data snooping by evaluating the performance of the best trading rule in the context of the full 'universe' of rules. The best trading rule is found by searching over the full set of trading rules and selecting the rule that maximizes a pre-determined performance criterion (e.g. mean net return). The *p*-value for the best trading rule is found by simulating the asymptotic distribution of the maximum of the performance measure across the full universe of trading rules. A reality check *p*-value for the best trading rule can be considered a 'data-snooping adjusted' *p*-value.

Sullivan *et al.* (1999) apply the bootstrap reality check methodology to the Dow Jones Industrial Average (DJIA) over 1897-1996. They adopt the same sample period (1897-1986) studied by Brock *et al.*

(1992) for in-sample tests and examine an additional 10 years from 1987-1996 for out-of-sample tests. S&P 500 index futures from 1984-1996 are also used to test the performance of trading rules. For the full set of technical trading rules, Sullivan *et al*. consider about 8,000 trading rules drawn from five technical trading systems: filters, moving averages, support and resistance, channel break-outs, and on-balance volume averages. Two performance measures are employed, mean return and Sharpe ratio. Zero mean profit and the risk-free interest rate are selected as benchmarks.

Results indicate that the best rule (a 5-day moving average rule) over 1897-1996 generates an annual mean return of 17.2% (a break-even transaction cost of 0.27% per trade). The bootstrap reality check *p*-value is zero, which indicates that the mean return is not the result of data snooping. Among the 26 trading rules examined by Brock *et al*. (1992), the best rule (50-day variable moving average rule with a 1% band) for the same sample period generates an annual mean return of 9.4% and a bootstrap reality check *p*-value of zero, suggesting their findings are robust to data snooping biases. Out-of-sample results are disappointing by comparison. Over the 10-year out-of-sample period (1987-1996), the best rule (a 5-day moving average rule) from the full universe over 1897-1986 generates a mean return of only 2.8% per year with a nominal *p*-value of 0.32, indicating that the best rule does not continue to generate an economically and statistically significant return in the subsequent period.[9] The best rule for the S&P 500 futures index over 1984-1996 generates a mean return of 9.4% per year and a bootstrap reality check *p*-value of 0.91, suggesting that the return is a result of data snooping. The poor out-of-sample performance of technical trading rules relative to in-sample performance led Sullivan *et al*. to conclude that the efficiency of stock markets had improved in recent years

Sullivan *et al*. (2003) enlarge the full set of trading rules by combining their earlier set of technical trading rules with calendar frequency trading rules first tested by Sullivan *et al*. (2001). The calendar frequency rules are designed to exploit calendar effects (e.g. the Monday effect, the holiday effect, and the January effect) documented in the finance literature. For DJIA data, the best of the augmented universe of trading rules (a 2-day-on-balance volume rule) generates an annual mean return of 17.1% over the full sample period, 1897-1998. The bootstrap reality check *p*-value is zero for the best trading rule and it outperforms a buy-and-hold strategy (annual mean return of 4.8%). However, over a recent period, 1987-1996, the best rule (a week-of-the-month strategy) generates only slightly higher mean returns (17.3% per year) than a buy-and-hold return (13.6%). Moreover, the return is statistically insignificant with a bootstrap reality check *p*-value of 0.98. Similar results are found for the S&P 500 futures data. Hence, Sullivan *et al*. (2003) argue that it may be premature to conclude that both technical trading rules and calendar rules outperform a buy-and-hold benchmark in the stock market. Qi and Wu (2002) also apply White's (2000) methodology to seven foreign exchange rates during 1973-1998 and find that technical trading rules generate substantial profits (7.2% to 12.2%) in five of the seven markets even after adjustment for transaction costs and systematic risk.

One issue with White's bootstrap methodology is the difficulty of constructing the full 'universe' of technical trading rules required by the methodology. Sullivan *et al*. (1999) assume that rules from five technical trading systems represent the full set of technical trading rules. However, there may be numerous different technical trading systems 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 included rules in the universe performed relatively well during the historical sample period.

Another issue is that the null hypothesis in White's bootstrap methodology consists of multiple inequalities, which leads 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. White solves this ambiguity in the null distribution by applying the least favorable configuration (LFC), also known as the points least favorable to the alternative hypothesis. However, Hansen (2003) shows that such a LFC-based test has limitations because it does not ordinarily meet an 'asymptotic similar condition' that is necessary for a test to be unbiased, and as a result, the test may be sensitive to the inclusion of poor forecasting models. Simulation and empirical evidence in Hansen's studies (2003, 2005) confirms that the inclusion of relatively few poor-performing models can severely reduce 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 for each trading system because there is no theoretical guidance with respect to the proper selection of parameters. If poor-performing trading rules are included, tests based on the White's procedure may produce downward biased *p*-values (see Hansen, 2003, 2005, for further discussion).

3.2.4. *Genetic Programming Studies*

Genetic programming (Koza, 1992) is a numerical optimization procedure 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 evolution over many successive generations under a given fitness (performance) criterion. Solution candidates that satisfy the fitness criterion are likely to reproduce, while ones that fail to meet the criterion are likely to be replaced. When applied to technical trading rules, the building blocks of genetic algorithms consist of various functions of past prices, numerical and logical constants, and logical functions.

The aforementioned features of genetic programming may provide some advantages relative to traditional approaches for testing technical trading rules. The traditional approach investigates a pre-determined parameter space of technical trading systems, while the genetic programming approach examines a search space composed of logical combinations of trading systems or rules. Thus, the fittest (or locally optimized) rules identified by genetic programming can be viewed as *ex ante* rules in the sense that their parameter values are not determined before the test. Since the procedure helps researchers avoid some of the arbitrariness involved in selecting parameters, it may reduce the risk of data snooping biases. Of course, potential bias cannot be completely eliminated because the search domain, i.e., trading systems, is still constrained to some degree in practice (Neely *et al*., 1997).

Allen and Karjalainen's (1999) study is among the first to apply genetic programming to test the profitability of technical trading rules. They investigate the daily S&P 500 index from 1928 through 1995 with logical combinations of moving averages and maxima and minima of past prices. To identify optimal trading rules, 100 independent trials are conducted by saving one rule from each trial (for the genetic algorithm, see Table 1 in Allen and Karjalainen, 1999, p. 256). The fitness criterion is the maximum excess return over a buy-and-hold strategy after accounting for transaction costs. Excess returns are calculated only on long positions and using several alternative 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 are employed. The 5-year training and 2-year selection periods begin in 1929 and are 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 is 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 are executed.

Out-of-sample results indicate that trading rules optimized by genetic programming fail to generate consistent excess returns over a simple buy-and-hold strategy after adjustment for transaction costs. After considering transaction costs of 0.25%, average excess returns are negative for 9 of the 10 periods. Even after lowering transaction costs to 0.10%, average excess returns are negative for 6 out of the 10 periods. For most test periods, only a few trading rules generate positive excess returns. However, in most of the training periods, the optimal trading rules show some forecasting ability because the difference between average daily returns during in- and out-of-the-market days is positive, and the volatility during 'in' days is generally lower than during 'out' days. Allen and Karjalainen (1999) conclude that the results are generally consistent with market efficiency.

Ready (2002) compares the performance of technical trading rules formed by genetic programming to Brock *et al*.'s (1992) moving average rules for dividend-adjusted DJIA data. Brock *et al*.'s best trading rule (1/150 moving average without a band) for the 1963-1986 period generates substantially higher excess returns than the average of trading rules identified by genetic programming after transaction costs. However, the moving average rule underperforms genetically optimized rules over 1957-1962. Thus, it seems unlikely that Brock *et al*.'s moving average rules would have been chosen by a hypothetical trader at the end of 1962. Moreover, the genetically optimized rules perform poorly for each out-of-sample period, i.e., 1963-1986 and 1987-2000. Ready (2002, p. 43) concludes that '…the apparent success (after transaction costs) of the Brock *et al.*'s (1992) moving average rules is a spurious result of data snooping'.

The results of other genetic programming studies are mixed. Wang (2000) and Neely (2003) report that genetically optimized trading rules fail to outperform a buy-and-hold strategy in both S&P 500 spot and futures markets. Neely (2003) shows that genetic trading rules produce negative mean excess returns over a buy-and-hold strategy during the entire out-of-sample period, 1936-1995. In contrast, Neely *et al*. (1997) and Neely and Weller (1999, 2001) report successful performance of genetic trading rules in foreign exchange markets, although trading profits appear to gradually decline over time. Neely and Weller's (2001) findings indicate that technical trading profits net of transaction costs for four major foreign exchange rates (i.e., mark, yen, pound, Swiss franc) range from 1.7%-8.3% per year over 1981-1992, but are near zero or negative, except for the yen, over 1993-1998. Using intra-day data for 1996 and realistic trading hours and transaction costs, Neely and Weller (2003) generate break-even transaction costs of less than 0.02% for most major foreign exchange rates using genetic trading rules. Roberts (2003) finds that genetic trading rules generate a statistically significant mean net return (a daily mean return of $1.07 per contract) in comparison to a buy-and-hold return (-$3.30) in wheat futures over 1978-1998. For corn and soybean futures markets, however, genetic trading rules produce both negative mean returns and negative ratios of profit to maximum drawdown. In sum, technical trading rules formulated by genetic programming appear to be unprofitable in stock markets, particularly in recent periods. In contrast, the rules perform better in foreign exchange markets, but their performance may have decreased over time. For grain futures markets, performance is partially successful.

Since rules are chosen using price data available before the beginning of the test period, the genetic programming approach may avoid data snooping problems caused by *ex post* selection of technical trading rules. However, genetic programming studies may be subject to other forms of data snooping. In particular, application of genetic programming to sample periods before the initial development of the procedure violates the market efficiency conditions proposed by Timmermann and Granger (2004, p.16). That is, the set of forecasting models, estimation methods, and the search technology used to select the best (or a combination of best) forecasting model(s) at any point in time must have actually been available for use by market participants. In addition, trading rules formulated by genetic programming generally have a more complex structure than that of typical trading rules used by technical analysts. This suggests that the rules do not approximate real technical trading rules applied in practice.

3.2.5. *Non-linear Studies*

Motivation for non-linear studies comes from the fact that the popular linear models analyzed by Brock *et al*. (1992) fail to explain the temporal dynamics of technical trading returns (Gençay and Stengos, 1997, p. 25). Non-linear studies attempt to directly measure the profitability or predictability of a trading rule derived from a non-linear model, such as a feed-forward neural network or a nearest neighbor regression. These studies typically incorporate lagged raw returns or past trading signals from a technical trading rule into a non-linear model. Gençay (1998a) tests the profitability of technical trading rules based on a feed-forward neural network using DJIA data for 1963-1988. Across six sub-periods, the trading rules generate annual net returns of 7%-35% and easily outperform a buy-and-hold strategy. Similar results are found for the Sharpe ratio criterion. Hence, technical trading rules based on non-linear models outperform the buy-and-hold strategy after transaction costs and risk are taken into account. In addition, correct sign predictions for the recommended positions range from 57% to 61%.

Gençay (1998b, 1999) investigates the non-linear predictability of asset returns further by incorporating past trading signals from technical trading rules, i.e., moving average rules, or lagged returns into a feed-forward neural network or nearest neighbor regression. Out-of-sample results in terms of correct sign predictions and mean square prediction error (MSPE) indicate that, in general, both the feed-forward network model and the nearest neighbor model provide substantial forecast improvement and outperform the random walk model or GARCH (1,1) model in both stock and foreign exchange markets. In particular, non-linear models based on past buy and sell signals of moving average rules provide more accurate predictions than those based on past returns. Gençay and Stengos (1998) extend previous non-linear studies by incorporating a 10-day volume indicator into a feed-forward neural network model as an additional regressor. For the same DJIA data as used in Gençay (1998a), the non-linear model produces a 12% forecast gain over the benchmark (an OLS model with lagged returns as regressors) and provides much higher correct sign predictions (an average of 62%) than other linear and non-linear models.

Fernández-Rodríguez *et al*. (2000) apply a feed-forward neural network to the Madrid Stock index, finding that a technical trading rule based on the feed-forward network outperforms a buy-and-hold strategy before transaction costs. Sosvilla-Rivero *et al*. (2002) also show that technical trading rules based on a nearest neighbor regression earn net returns during 1982-1996 of 35% and 28% for the mark and yen, respectively. They also demonstrate that eliminating U.S. intervention days decreases net returns substantially, to -10% and -28% for the mark and yen, respectively. Fernández-Rodríguez *et al*. (2003) find that trading rules based on the nearest neighbor model are superior to moving average rules in European exchange markets for 1978-1994. The non-linear trading rules generate statistically significant annual net returns of 1.5%-20.1% for the Danish krona, French franc, Dutch guilder, and Italian lira.

However, Hamm and Brorsen (2000) develop a neural network trading model for hard red winter wheat and mark futures and find unfavorable results. With lagged prices as inputs to the neural network, they cannot reject the null hypothesis that gross or net trading returns are less than or equal to zero.

Non-linear studies generally provide positive evidence about the usefulness of technical trading rules in stock and foreign exchange markets. However, non-linear studies have a similar problem to that of genetic programming studies. That is, as suggested by Timmermann and Granger (2004), it may be inappropriate to apply a non-linear approach developed in recent years to reveal the profitability of technical trading rules in the 1970s or 1980s. Gencay and Stengos (1997) also show that simple methods such as the one-step ahead nearest neighbor estimator provide better forecasts than more complex neural network models. Finally, neural network solutions are not unique, which makes it difficult to replicate the results of previous studies.

3.2.6. *Chart Pattern Studies*

Chart pattern studies test the profitability or forecasting ability of visual chart patterns commonly used by technical analysts. Familiar chart patterns, with names typically derived from their shapes in bar charts, are gaps, spikes, flags, pennants, wedges, saucers, triangles, head-and-shoulders, and various tops and bottoms (e.g. Edwards and Magee, 1996; Schwager, 1996; Pring, 2002). In an early study, Levy (1971) investigates the profitability of 32 five-point chart formations for NYSE securities. He finds that none of the 32 patterns generates greater than average profits for any holding period.

Chang and Osler (1999) provide a rigorous study of chart patterns. They evaluate the performance of head-and-shoulders patterns using daily spot rates for six foreign exchange markets (the mark, yen, pound, franc, Swiss franc, and Canadian dollar) during the floating rate period of 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 a straight line connecting the troughs separating the head from right and left shoulders is ‘the neckline.’ Head-and-shoulders can occur both at peaks and at troughs, where they are called ‘tops’ and ‘bottoms’, respectively. Chang and Osler (1999) formulate an algorithm for head-and-shoulders identification and then establish a strategy for entering and exiting positions based on such recognition. The entry position is taken when price breaks the neckline, while the timing of exit is determined by stop-loss, bounce possibility, or particular holding periods.

Chang and Osler find that head-and-shoulders rules generate statistically significant returns of about 13% and 19% per year for the mark and yen, respectively, but not for other exchange rates. The trading returns are substantially higher than either the annual buy-and-hold returns or the annual average return (6.8%) on the S&P 500 index over the sample period. Returns for the mark and yen also are significantly greater than those derived from 10,000 simulated random walk bootstrap samples and remain substantial even after subtracting transaction costs of 0.05% per round-trip, incorporating interest differentials, and adjustment for risk. Trading returns for the mark and yen also appear 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 a random walk. However, the observed performance of head-and-shoulders rules appears to be easily dominated by the performance of moving average and momentum rules in terms of total (accumulated) profits and Sharpe ratios. The simple technical trading rules generate statistically significant and substantially larger returns than the head-and-shoulder rules for all six foreign exchange rates.

Lo *et al*. (2000) evaluate the usefulness of 10 chart patterns in predicting stock prices: the head-and-shoulders and inverse head-and-shoulders, broadening tops and bottoms, triangle tops and bottoms, rectangle tops and bottoms, and double tops and bottoms. For NYSE/AMEX stocks, goodness-of-fitness test results indicate that relative frequencies of returns conditional on signals from 5 of the 10 chart patterns are significantly different from relative frequencies of unconditional returns. In contrast, all 10 patterns are statistically significant for Nasdaq stocks. Volume trends provide little incremental information for both stock markets. Lo *et al*. (2000, p. 1753) conclude, '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'. Dawson and Steeley (2003) apply Lo *et al*.'s approach to U.K. stock data and show that 'informativeness' of chart patterns does not necessarily lead to trading profits. They find that average market-adjusted returns are negative for the technical patterns, even though return distributions conditional on chart pattern signals are significantly different from unconditional distributions.

Caginalp and Laurent (1998) report that 'candlestick' reversal patterns generate substantial profits in stock markets compared to a buy-and-hold strategy. Specifically, down-to-up reversal patterns produce an average return of 0.9% during a two-day holding period for S&P 500 stocks over 1992-1996. Leigh, Paz, and Purvis (2002) and Leigh *et al*. (2002) find that bull flag patterns generate positive excess returns (before transaction costs) for the NYSE Composite Index over a buy-and-hold strategy. However, Curcio *et al*. (1997), Guillaume (2000), and Lucke (2003) all show limited evidence of the profitability of technical patterns in foreign exchange markets, with trading profits from the patterns declining over time (Guillaume, 2000). Overall, the results of chart pattern studies vary depending on patterns, markets, and sample periods tested, but suggest that some chart patterns might be profitable in stock and foreign exchange markets. Nevertheless, all studies in this category, except for Leigh, Paz, and Purvis (2002), do not conduct parameter optimization and out-of-sample tests and do not address data snooping problems.

3.2.7. *Other Studies*

Studies in this category do not fit neatly in any of the previous categories. They are most similar to early studies, in that trading rules generally are not optimized, out-of-sample verification typically is not undertaken, and data snooping problems are ignored. For example, Neely (1997) tests the profitability of filter rules and moving average rules on four major exchange rates (the mark, yen, pound sterling, and Swiss franc) over 1974-1997. The results indicate that trading rules yield positive net returns in 38 of the 40 cases after deducting transaction costs of 0.05% per round-trip. However, Neely argues that the apparent success of the technical trading rules did not necessarily violate market efficiency because of problems in testing procedures, such as difficulty in obtaining actual prices and interest rates, the absence of a proper measure of risk, and data snooping.

Pruitt and White (1988) and Pruitt, Tse, and White (1992) document that a combination system consisting of cumulative volume, relative strength, and moving averages (CRISMA) was profitable in stock markets. For example, Pruitt, Tse, and White report that the CRISMA system outperforms a buy-and-hold strategy over 1986-1990. Annual excess returns are estimated to be 1.0%-5.2% after transaction costs of 2%. Sweeney (1988) and Corrado and Lee (1992) show that filter-based rules outperform buy-and-hold strategies after transaction costs in stock markets. Irwin *et al.* (1997) compare the performance of the channel 'break-out' trading system to ARIMA models in soybean-complex futures markets. During the out-of-sample period (1984-1988), channel systems generate statistically significant mean returns ranging 5.1%-26.6% and outperform a trading strategies based on ARIMA model forecasts.

Overall, studies in this category indicate that technical trading rules perform well in stock markets, foreign exchange markets, and grain futures markets. As noted above, however, these studies typically omit trading rule optimization and out-of-sample verification and do not address data snooping problems.

3.2.8. *Summary of Modern Studies*

Table 3 summarizes the results of modern studies.[10] As shown in the table, the number of studies that identify positive technical trading profits is far greater than the number of studies that find negative profits. Among a total of 95 modern studies, 56 studies find profitability (or predictability) of technical trading strategies, while 20 studies report negative results. The rest (19 studies) indicate mixed results. In each of the three market categories (stock markets, foreign exchange markets and futures markets), the number of profitable studies is at least twice that of unprofitable studies. While modern studies indicate that technical trading strategies yielded economic profits in U.S. stock markets through the late 1980s, they failed to do so thereafter (Bessembinder and Chan, 1998; Sullivan *et al*., 1999; Ready, 2002). Several studies find 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 generated economic profits over the last few decades, although some recent studies suggest that technical trading profits have declined or disappeared since the early 1990s (Marsh, 2000; Neely and Weller, 2001; Olson, 2004; Sapp, 2004). For futures markets, technical trading strategies appear to be profitable between the mid-1970s and the mid-1980s. No study has comprehensively tested the profitability of technical trading strategies in futures markets using more recent data.

4. Explanations for Technical Trading Profits

Previous empirical studies suggest that technical trading rules may generate positive profits in certain speculative markets, most notably in foreign exchange and futures markets. Various theoretical and empirical explanations have been proposed for technical trading profits. In theoretical models, technical trading profits may arise because of market 'frictions', such as noise in current equilibrium prices, traders' sentiments, herding behavior, market power, or chaos. Empirical explanations focus on technical trading profits as a consequence of central bank interventions (particularly, in foreign exchange markets), order flow, temporary market inefficiencies, risk premiums, market microstructure deficiencies, or data snooping. Although these issues are still controversial, a thorough discussion is necessary to better understand the current state of the literature on technical analysis.

4.1. *Theoretical Explanations*

4.1.1. *Noisy Rational Expectations Models*

Under the standard model of market efficiency, the current equilibrium price fully reflects all available information and price adjusts instantaneously to new information. A basic assumption of the market efficiency model is that participants are rational and have homogeneous beliefs about information. Under a noisy rational expectations equilibrium, 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, thereby allowing the possibility of profitable trading opportunities.

Grossman and Stiglitz (1976, 1980) represent the most influential work on noisy rational expectations equilibrium models. They demonstrate that no agent in a competitive market has an incentive to collect and analyze costly information if current price reflects all available information, and as a result the competitive market breaks down. However, Grossman and Stiglitz's model supports weak-form market efficiency in which no profits are made based on price history (i.e., technical analysis) because it is assumed that uninformed traders have rational expectations. In contrast, models developed by Hellwig (1982), Brown and Jennings (1989), Grundy and McNichols (1989), and Blume *et al*. (1994) allow past prices to carry useful information for achieving positive profits in a speculative market.

Brown and Jennings (1989) propose a two-period noisy rational expectations model in which the current price is dominated as an information source by a weighted average of past and current prices. More specifically, 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. Noise in the current equilibrium price does not allow full revelation of all publicly available information available in 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.

As another example, Blume *et al*. (1994) propose an equilibrium model that emphasizes the informational role of volume. Unlike previous equilibrium models that consider the aggregate supply of a risky asset as the source of noise, their model assumes the source of noise is the quality of information. Blume *et al*. show 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. Technical analysis is valuable because current market statistics may be insufficient to reveal all information.

4.1.2. *Behavioral Models*

In the early 1990s, financial economists began to develop the field of behavioral finance, which is, '…finance from a broader social science perspective including psychology and sociology' (Shiller, 2003, p. 83). There are two types of investors in a typical behavioral finance model: arbitrageurs (also called sophisticated investors or smart money traders) 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). Behavioral (or feedback) models are based on two key assumptions. First, noise traders' demand for risky assets is affected by irrational beliefs or sentiments that are not fully justified by news or fundamental factors. Second, arbitrage, defined as trading by fully rational investors not subject to sentiment, is risky and limited because arbitrageurs are likely to be risk-averse (Shleifer and Summers, 1990, p. 19).

Noise traders buy when prices rise and sell when prices fall, like technical traders or 'trend chasers.' For example, when noise traders follow positive feedback strategies (buy when prices rise), this increases aggregate demand for an asset and results in a further price increase. Arbitrageurs may conclude that the asset is mis-priced and above its fundamental value, and therefore sell it short. According to De Long *et al*. (1990a), however, this form of 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 will become even more optimistic. As long as such risks are created by the unpredictability of noise traders' opinions, arbitrage by sophisticated investors will be reduced even in the absence of fundamental risk. A consequence is that sophisticated or rational investors 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 much later when price rises even higher. Therefore, although arbitrageurs ultimately force prices to return to fundamental levels, in the short run they amplify the effect of noise traders (De Long *et al*., 1990b).[11]

In feedback models, noise traders may be more aggressive than arbitrageurs due to overly-optimistic (or overly-pessimistic) views on markets, and thus bear more risk with associated higher expected returns. Despite excessive risk taking and consumption, noise traders may survive as a group in the long-run and dominate the market in terms of wealth (De Long *et al*., 1991; Slezak, 2003). Hence, 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).

4.1.3. *Herding Models*

Froot *et al*. (1992) show that herding behavior of short-horizon traders can result in informational inefficiency. In their model, informed traders who want to buy or sell in the near future can benefit from their information only if it is subsequently impounded into the price by the trades of similarly informed speculators. Therefore, traders having short horizons will make profits when they can coordinate their trading based on the same or similar information. This kind of positive informational spillover can be so powerful that 'herd' traders may even analyze information that is not closely related to the asset's long-run value. Technical analysis is one example. Froot *et al*. (1992, p. 1480) argue that, '…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'.

Introducing a simple agent-based model for market price dynamics, Schmidt (2002) shows that if technical traders are capable of affecting market liquidity, their concerted actions can move the market price in a direction favorable to their strategy. The model assumes a constant total number of traders consisting of 'regular' traders and 'technical' traders. Price moves linearly with excess demand, which in turn is proportional to the excess number of buyers drawn from both regular and technical traders. In the absence of technical traders, price dynamics form slowly decaying oscillations around an asymptotic value. However, inclusion of technical traders in the model increases the amplitude of price oscillations. The rationale behind this result is as follows: if technical traders believe price will fall, they sell, and thus, excess demand decreases. As a result, price decreases and the chartist component forces regular traders to sell. This leads price to decrease further until the fundamentalist priorities of regular traders become dominant again. The opposite situation occurs if technical traders make a buy decision based on their analysis.

4.1.4. *Chaos Theory*

Clyde and Osler (1997) provide another theoretical foundation for technical analysis by showing that charting methods may be equivalent to non-linear forecasting methods for high dimension (or chaotic) systems. They tested this idea by applying the identification algorithm for a 'head-and-shoulders' pattern to simulated high-dimension non-linear price series. More specifically, the following two hypotheses were tested: (1) technical analysis has no more predictive power on non-linear data than it does on random data; (2) when applied to non-linear data, technical analysis earns no more hypothetical profits than those generated by a random trading rule. Results shows that hit ratios (proportion of positions with positive gross profits) exceed 0.50 in almost all cases. Moreover, profits of the head-and-shoulders pattern on the non-linear data are higher than the median of those on the bootstrap simulated data in almost all cases. Thus, the first hypothesis is rejected. Hit ratio tests also reject the second hypothesis. Hence, technical analysis performs better on non-linear data than on random data and generates more profits than a random trading rule.

Additional research by Stengos (1996) shows that very large sample sizes may be needed to produce accurate forecasts with the simplest low dimension chaotic processes, depending on the specification of the non-linear process. Hence, tests of the forecasting ability of technical trading rules on non-linear price data may be sensitive to assumptions regarding the underlying data generating process.

4.2. *Empirical Explanations*

4.2.1. *Central Bank Intervention*

In the literature on technical analysis in foreign exchange markets, many authors have conjectured that technical trading profits are correlated with central bank intervention (Dooley and Shafer, 1983; Sweeney, 1986; Lukac *et al*., 1988; Davutyan and Pippenger, 1989; Levich and Thomas, 1993; Silber, 1994). The logic behind this idea is summed up by Saacke (2002, p. 467) as follows:

> After an exogenous shock to fundamentals, the exchange rate would, without central bank interventions, jump to a new equilibrium level (e.g. Dornbusch overshooting). Wishing to reduce volatility, central banks try to prevent the exchange rate from jumping by leaning against the wind. Thereby they delay the adjustment of the exchange rate. If

> adjustment is delayed, exchange rates will display a trend during the phase of adjustment. This trend may then be picked up and exploited by trend-following forecasters,….

In recent years, this idea has been formally tested with direct and indirect intervention data. Szakmary and Mathur (1997) use monthly foreign exchange reserves held by central banks as a proxy for intervention and find that profits for moving average rules in major foreign exchange markets may be explained by a 'leaning against the wind' policy of central banks. LeBaron (1999) uses daily official intervention series to show that when a typical moving average rule generates buy signals for a foreign exchange rate, the Federal Reserve tends to support the dollar the next period. This finding is consistent with a 'leaning against the wind' policy. He also finds that removal of intervention periods greatly reduces Sharpe ratios for moving average rules. LeBaron's (1999) findings are generally confirmed by subsequent studies (Neely and Weller, 2001; Neely, 2002; Saacke, 2002; Sosvilla-Rivero *et al*., 2002; Sapp, 2004). For example, using both Fed and Bundesbank intervention data, Saacke (2002) shows that moving average rules generate substantial returns on days when central banks intervene and during intervention periods. However, trading returns on days that neither coincide with nor are preceded by intervention periods are also quite substantial, strongly suggesting that interventions are not the only source of technical trading returns in foreign exchange markets. Moreover, Neely and Weller (2001) and Neely (2002) find that abnormally high returns of technical trading rules precede interventions and argue that interventions do not generate technical trading returns but rather respond to strong trends in exchange rates from which trading rules have already profited. In sum, all the above studies suggest that technical trading rules are profitable just before and during the intervention periods. The result suggests that central bank interventions are connected with technical trading returns in some way, even if they may not directly cause technical trading returns. It is interesting to note that both technical trading profits and central bank interventions in foreign exchange markets declined simultaneously after the mid-1990s (Sapp, 2004).

4.2.2. *Order Flow*

In a recent paper, Osler (2003) explains predictions of technical analysis in the foreign exchange market by order flows clustering at round numbers. Using stop-loss and take-profit orders placed at a large bank in three foreign exchange pairs (dollar-yen, dollar-U.K. pound, and euro-dollar), two widely used predictions of technical analysis are examined: (1) down-trends (up-trends) tend to reverse course at predictable support (resistance) levels, which are often round numbers, and (2) trends tend to be unusually rapid after rates cross support and resistance levels that can be identified *ex ante*. Since Brock *et al*. (1992) show that support and resistance levels (trading range break-out rules) possess predictive power in the stock market, these predictions may be applicable beyond the foreign exchange market.

Osler (2003) finds two critical asymmetries in the data that support the predictions of technical analysis. The first is that executed take-profit orders cluster more strongly at numbers ending in 00 than executed stop-loss orders. The second is that executed stop-loss buy (sell) orders are more strongly clustered just above (below) round numbers. According to Osler, clustering of order flows at round numbers is possible because: (1) the use of round numbers reduces the time and errors incurred in the transaction process; (2) round numbers may be easier to remember and to manipulate mentally; and (3) people may simply prefer round numbers without any reasoning.

Kavajecz and Odders-White (2004) provide a similar explanation for support and resistance levels by estimating limit order books in the stock market (i.e., NYSE) and analyzing the relation to support and resistance. Regression results show that support and resistance levels are positively and statistically significantly correlated with high cumulative depth, even after controlling for other current market conditions. In particular, technical indicator levels are statistically significant for 42% to 73% of the stocks when measures of cumulative depth in the limit order book such as mode and near depth ratio are used as the dependent variable. Furthermore, the results of Granger causality tests and analyses on the flow of newly placed limit orders suggest that support and resistance levels tend to identify clusters of orders (high depth) already in place on the limit order book.

Kavajecz and Odders-White also show that buy (sell) signals of moving average rules, generated when the short moving average penetrates the long moving average from above (below), correspond to a shift in quoted prices toward sell-side (buy-side) liquidity levels and away from buy-side (sell-side) levels. That is, moving average signals appear to uncover information about the 'skewness' of liquidity between the two sides of the limit order book. Hence, Kavajecz and Odders-White (2004, p. 1066) conclude that, '…the connection between technical analysis and limit order book depth is driven by technical analysis being able to identify prices with high cumulative depth already in place on the limit order book'. The explanation of technical trading profits by order flows is corroborated in recent years by the fact that order flow analysis has gained in popularity among foreign exchange traders (Gehrig and Menkhoff, 2003, 2004).

4.2.3. *Temporary Market Inefficiencies*

Several recent studies (e.g. Sullivan *et al*., 1999, 2003; Olson, 2004) report that technical trading rules generate positive economic profits before the 1990s, but the profits decline substantially or disappear altogether in subsequent years. Such results may be explained by temporary market inefficiencies in periods before the 1990s. There are two possible explanations for the temporary inefficiencies. The first is the self-destructive nature of technical trading rules. Timmermann and Granger (2004, p. 26) state that, 'Ultimately, there are likely to be short-lived gains to the first users of new financial prediction methods. Once these methods become more widely used, their information may get incorporated into prices and they will cease to be successful'. Several studies (e.g. Dimson and March, 1999; Schwert, 2003; Marquering *et al.*, 2006) demonstrate that many of the well-known market anomalies in the stock market attenuate, disappear, or reverse after they are documented in the academic literature. In the literature on technical trading rules, several prominent studies (e.g. Sweeney, 1986; Taylor, 1986; Lukac *et al*., 1988; Brock *et al*., 1992), all of which document substantial technical trading profits, were published during the mid-1980s and the early 1990s. In this context, an increase in the use of technical trading rules among investors and traders over the 1990s may have lowered or even eliminated profitable technical trading opportunities. The massive increase in hedge fund and CTA investment during the 1990s is consistent with this argument. Investment in CTAs (and other 'managed' futures accounts) alone increased from about $7 billion at the beginning of the decade to over $40 billion at the end.[12]

The second possible explanation of temporary inefficiencies is structural change in markets. At a basic level, all technical trading rules depend on some form of sluggish reaction to new information as it enters the market. Structural changes in markets have the potential to alter the speed with which prices react to information and reach a new equilibrium. For example, cheaper computing power, the rise of electronic trading and advent of discount brokerage firms has probably lowered transaction costs and increased liquidity in many markets (Sullivan *et al*., 1999). These changes may have increased the speed of market price movements, and in turn, reduced the profitability of technical trading rules. Kidd and Brorsen (2004) also argue that economy-wide changes, such as freer trade, better economic predictions and fewer major shocks to the economy, lower price volatility and the corresponding demand for technical speculators to move markets to equilibrium. In order to test this hypothesis, Kidd and Brorsen compute sample statistics for 17 futures markets across 1975-1990 and 1991-2001. Price volatility generally decreases across the two periods and kurtosis (extremeness) of price changes increases while markets are closed. The authors argue that both changes are consistent with a reduction in the profitability of technical analysis due to economy-wide structural changes.

4.2.4. *Risk Premiums*

Positive technical trading profits may be compensation for bearing risk. Although a universally-accepted model of risk is not available, the Sharpe ratio of excess returns to standard deviation has been widely used in studies of technical analysis as a risk-adjusted performance measure. To determine whether technical trading returns are abnormal on a risk-adjusted basis, Sharpe ratios of technical trading rules are often compared to that of a benchmark strategy such as a buy-and-hold strategy. However, many studies find that technical trading rules generate higher Sharpe ratios than the benchmarks, particularly in futures markets and foreign exchange markets (e.g. Lukac and Brorsen, 1990; Chang and Osler, 1999; LeBaron, 1999).

The capital asset pricing model (CAPM) provides another risk-adjusted performance measure. While most studies that have estimated risk-adjusted returns using the CAPM assume a constant risk premium over time, a few studies test whether technical trading returns can be explained by time-varying risk premiums. In the majority of studies, it turns out that a constant risk premium fails to explain technical trading returns (e.g. Sweeney, 1986; Lukac *et al.*, 1988; Taylor, 1992; Levich and Thomas, 1993; Neely *et al.*, 1997). Results for time-varying premiums are mixed. Taylor (1992) investigated whether returns on a portfolio of optimal technical trading rules in foreign exchange futures markets are compensation for bearing time-varying risk premiums. Through preliminary tests based on McCurdy and Morgan's (1992) work, he finds that time-varying risk premiums cannot explain excess returns of technical trading rules. Okunev and White (2003) report a similar result in which trading profits for their return-based relative strength rules (also called a momentum strategy) are not a reward for bearing time-varying risk. In contrast, Kho (1996) and Sapp (2004) show that a large part of technical trading returns on foreign exchange markets can be explained by time-varying risk premiums estimated from versions of the conditional CAPM. These seemingly contradictory results may be caused by different data frequencies (daily, weekly, or monthly), asset pricing model specifications, market proxies, technical trading systems, and other testing procedures.

It should be noted that the above risk measures have several 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. The CAPM is also known to have a joint hypothesis problem. Namely, when abnormal returns (positive intercept) are found, researchers cannot differentiate whether markets are truly inefficient or the CAPM is mis-specified. It is well-known that the CAPM and other multifactor asset pricing models, such as the Fama-French three factor model, are subject to mis-specification problems (Fama, 1998).

4.2.5. *Market Microstructure Deficiencies*

Technical trading rule profits can be exaggerated by using unrealistically low transaction costs and disregarding other market microstructure-related factors. 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 are introduced by Roll (1984), Thompson and Waller (1987), and Smith and Whaley (1994). However, these estimators may not work particularly well in approximating actual bid-ask spreads if the assumptions underlying the estimators do not correspond to the actual market microstructure (Locke and Venkatesh, 1997). Data on actual bid-ask spreads reflects true market-impact effects, or the effect of trade size on market price. Market-impact arises in the form of price concessions for large trades (Fleming *et al*., 1996). The magnitude of market-impact depends on the liquidity and depth of a market. To date, only one study has directly estimated market impact (slippage) costs for technical traders. Greer *et al*. (1992) examine the transactions of a commodity futures fund in the mid-1980s that uses trend-following technical systems to signal trades. They report that execution costs (slippage) average about $40 per trade, much larger than costs estimates based on statistical bid-ask estimators. In lieu of obtaining appropriate data sources regarding bid-ask spreads, plausible alternatives include the use of transaction costs greater than the actual historical commissions (Schwager, 1996) or assuming several possible scenarios for transaction costs.

Other market microstructure factors that may affect technical trading returns are non-synchronous trading and daily price limits. Technical trading studies typically assume that trades can be executed at closing prices on the day when trading signals are generated. However, Day and Wang (2002, p. 433) investigate the impact of non-synchronous trading on technical trading returns for the DJIA and argue 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'. This problem may be mitigated by using either the estimated 'true' closing levels for asset prices (e.g. Day and Wang, 2002) or the next day's closing prices (e.g. Brock *et al*., 1992; Taylor, 1992; Bessembinder and Chan, 1998). In addition, 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 generally imply that buy (sell) trades will be actually executed at higher (lower) prices than those at which trading signals were generated. This may result in seriously overstated trading returns if trades are assumed to be executed at the 'locked' limit price levels.

4.2.6. *Data Snooping*

As summarized in previous sections, studies that find positive technical trading returns (e.g. Brock *et al*., 1992) have been challenged by subsequent studies because of apparent deficiencies in testing procedures. One of the most controversial issues is data snooping. According to White (2000, p, 1097), '…data snooping occurs when a given set of data is used more than once for purposes of inference or model selection'. When such data snooping occurs, any successful results may be spurious because they could be obtained just by chance. More specifically, data snooping results in overstated significance levels for conventional hypothesis tests, which can lead to incorrect statistical inference (e.g. Lovell, 1983; Denton, 1985; Lo and MacKinlay, 1990). A number of authors discuss data snooping problems in studies of technical analysis (Jensen, 1967; Jensen and Benington, 1970; Brock *et al*., 1992; Neely *et al*., 1997; Bessembinder and Chan, 1998; Allen and Karjalainen, 1999; Sullivan *et al*., 1999, 2003; White, 2000; Ready, 2002).

In testing technical trading rules, a fairly blatant form of data snooping is an *ex post* and 'in-sample' search for profitable trading rules, a distinctive feature of several early studies. Cooper and Gulen (2004) suggest that more subtle forms of data snooping arise when a set of data is repeatedly used to search for profitable choice variables, which in the present context include 'families' of trading systems, markets, in-sample estimation periods, out-of-sample periods, and trading model assumptions such as performance criteria and transaction costs. Consider 'standard' studies as an example. Even though these studies optimize trading rules in-sample and trace the out-of-sample performance of optimal rules, a researcher may obtain a successful result by deliberately investigating a number of combinations of in- and out-of-sample optimization periods and selecting the combination that provides the most favorable result. Prior selection of only one combination of in- and out-of-sample periods may be a safeguard, but this selection is also likely to be strongly affected by similar previous research.

A different form of data snooping occurs when researchers consider only popular trading rules, as in Brock *et al*. (1992). Since Brock *et al*.'s moving average and trading range break-out rules have obtained their popularity over a long history they are likely to be subject to 'survivorship' bias. In other words, if a large number of trading rules have been investigated over time some rules may produce abnormal returns by chance even though they do not possess genuine forecasting power. Statistical inference based only on the surviving trading rules may cause a form of data snooping bias because it does not account for the full set of initial trading rules, most of which are likely to have performed poorly (Bessembinder and Chan, 1998; Sullivan *et al*., 1999, 2003).

As noted in earlier sections, still another form of data snooping is the application of a new search procedure, such as genetic programming or nearest neighbor neural networks, to sample periods before the development of the procedure (Cooper and Gulen, 2004; Timmermann and Granger, 2004). Cooper and Gulen (2004, p. 7) argue that, '…it would be inappropriate to use a computer intensive genetic algorithm to uncover evidence of predictability before the algorithm or computer was available'. Most genetic programming studies and non-linear studies are subject to this problem.

5. Summary and Conclusions

Numerous empirical studies examine the profitability of technical trading rules over the last four decades. In this survey, the empirical literature is categorized into two groups, 'early' studies (1960-1987) and 'modern' studies (1988-2004) depending on testing procedures. The results of early studies vary from market-to-market. In general, early studies of stock markets show limited evidence of the profitability of technical trading rules, while studies of foreign exchange markets and futures markets frequently find sizable net profits. However, early studies exhibit several limitations in their testing procedures. Only one or two trading systems are considered, risk of trading rules is often ignored, statistical tests of return significance generally are not conducted, parameter (trading rule) optimization and out-of-sample verification are not employed, and data snooping problems are not given serious attention.

Modern studies improve upon the limitations of early studies and typically increase the number of trading systems tested, assess risks of trading rules, perform statistical tests with either conventional statistical tests or more sophisticated bootstrap methods, or both, and conduct parameter optimization and out-of-sample verification. Modern studies are sorted into seven groups on the basis of their distinctive features: (i) standard; (ii) model-based bootstrap; (iii) reality check; (iv) genetic programming; (v) non-linear; (vi) chart patterns; and (vii) other. Among a total of 95 modern studies, 56 studies find positive results regarding technical trading strategies, 20 studies obtain negative results, and 19 studies indicate mixed results. Modern studies also indicate that technical trading rules yielded economic profits in U.S. stock markets until the late 1980s, but not thereafter. In foreign exchange markets, technical trading rules were profitable at least until the early 1990s. Technical trading rules applied to futures markets were profitable until the mid-1980s.

Technical trading profits in the 1970s and 1980s can be explained by several theoretical models and/or empirical regularities. Noisy rational expectations equilibrium models, feedback models and herding models postulate that price adjusts sluggishly to new information due to noise in the market, traders' sentiments or herding behavior. Under chaos theory, technical analysis may be equivalent to a method for non-linear prediction in a high dimension (or chaotic) system. Various empirical factors, such as central bank interventions, clustering of order flows, temporary market inefficiencies, time-varying risk premiums, market microstructure deficiencies, and data snooping biases, have also been proposed as the source or explanation for technical trading profits.

Notwithstanding the positive evidence about profitability, improved procedures for testing technical trading strategies, and plausible theoretical explanations, many academics still appear to be skeptical about technical trading rules. For example, in a recent textbook on asset pricing, Cochrane (2001, p. 25) 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'. This statement suggests the skepticism is based on data snooping problems and potentially insignificant economic profits after appropriate adjustment for transaction costs and risk.

There are two basic approaches to addressing the problem of data snooping. The first is to simply replicate a previous study on a new set of data (e.g. Lo and MacKinlay, 1990; Schwert, 2003). This approach is borrowed from the classical experimental approach to generating scientific evidence. That is, if similar results are found using new data and the same procedures as in the original study, more confidence can be placed in the original results.[13] To date, only one previous study replicates earlier technical trading results on new data (Sullivan *et al.*, 1999). For purposes of replication, 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 'written in stone' at the point in time the study was published, and (3) the publication date of the original work should be sufficiently far in the past that a follow-up study can have a reasonable sample size. The second approach for dealing with data snooping is White's (2000) bootstrap reality check methodology, which has been applied in only three studies to date (Sullivan *et al.*, 1999, 2003; Qi and Wu, 2002). White's methodology provides 'data-snooping adjusted' *p*-values for the best trading rule out of the full universe considered. Further research is needed using both the replication and reality check approaches in order to provide more conclusive evidence on the profitability of technical trading rules.

Treatment of risk and market microstructure issues also needs to be addressed in future studies. Risk is difficult to assess because each risk measure has its own limitations and all are subject to a joint hypothesis problem. Cochrane (2001, p. 465) suggests consideration of some version of a consumption-based model, such as Constantinides and Duffie's (1996) model with uninsured idiosyncratic risks or Campbell and Cochrane's (1999) habit persistence model. The market microstructure issues of bid-ask spreads and non-synchronous trading need careful attention as well. The advent of large and detailed transactions databases should allow considerable progress to be made in addressing these problems. Researchers should also incorporate accurate histories of daily price limits into technical trading models.

Finally, there remains a large and persistent gap between the views of many market participants and large numbers of academics about technical analysis.[14] In their recent survey study, Gehrig and Menkhoff (2003, p. 3) state that, 'According to our results, technical analysis dominates foreign exchange and most foreign exchange traders seem to be chartists now'. Shiller (1990, p. 55) also recognized the gap in his early questionnaire survey work on the stock market crash of 1987, pointing out that, 'Obviously, the popular models (the models that are used by the broad masses of economic actors to form their expectations) are not the same as those held by economists'. He asserts that, 'Once one accepts the difference, economic modeling cannot proceed without collecting data on the popular models themselves'. While similar efforts have been made in several studies on the use of technical analysis in the foreign exchange market (e.g. Taylor and Allen, 1992; Lui and Mole, 1998; Cheung and Chinn, 2001), few studies have directly surveyed technical traders in other speculative markets (e.g. Smidt, 1965b; Brorsen and Irwin, 1987). Moreover, popular models like technical analysis may differ across markets and through time. Therefore, researchers are strongly encouraged to directly elicit and analyze the views and practices of technical traders in a broad cross-section of speculative markets. This would provide a much richer understanding of the actual use of technical trading strategies in real-world markets.

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Table 1. Number of Technical Trading Studies, 1960-2004[a]

Year	Stock markets	Foreign exchange markets	Futures markets	Total	Relative frequency (%)
1960-1964	3	0	3	6	4.4
1965-1969	6	1	1	8	5.8
1970-1974	4	0	3	7	5.1
1975-1979	2	3	2	7	5.1
1980-1984	2	1	6	9	6.6
1985-1989	4	3	7	14	10.2
1990-1994	5	3	2	10	7.3
1995-1999	18	13	1	32	23.4
2000-2004[b]	22	20	2	44	32.1
Total	66	44	27	137	100.0

[a] Studies on equity (index) futures and options and foreign exchange futures are categorized into 'stock markets' and 'foreign exchange markets' studies, respectively. 'Futures markets' studies include studies on other individual futures markets or various groups of futures markets.

[b] Through August 2004.

Table 2. Categories for Modern Technical Analysis Studies, 1988-2004

			Criteria						
Category	Number of studies[a]	Representative study	Transaction costs	Risk adjustment	Trading rule optimization	Out-of-sample tests	Statistical tests	Data snooping addressed	Distinctive features
Standard	24	Lukac *et al*. (1988)	√	√	√	√	√		Conduct parameter optimization and out-of-sample tests.
Model-based bootstrap	21	Brock *et al*. (1992)		√			√		Use model-based bootstrap methods for statistical tests. No parameter optimization or out-of-sample tests conducted.
Reality check	3	Sullivan *et al*. (1999)		√	√	√	√	√	Use White's (2000) reality check bootstrap methodology for trading rule optimization and statistical tests.
Genetic programming	11	Allen and Karjalainen (1999)	√	√	√	√	√	√	Use genetic programming techniques to optimize trading rules.
Nonlinear	9	Gençay (1998a)	√	√	√	√	√		Use nearest neighbor and/or feedforward network regressions to generate trading signals.
Chart patterns	11	Chang and Osler (1999)	√	√			√		Use recognition algorithms for chart patterns.
Other	16	Neely (1997)	√	√			√		Generally lack trading rule optimization and out-of-sample tests and do not address data-snooping problems.

[a] The total number of modern studies is 95.

Table 3. The Profitability of Technical Trading Rules in Modern Studies, 1988-2004[a]

Studies	Number of studies: Positive	Mixed	Negative	Profit range	Comments
A. Stock markets					
Standard	2	2	2	4%-17%[b]	• For the Dow Jones Industrial Average (DJIA), which is most frequently tested series in the literature, results vary considerably depending on the testing procedure adopted. In general, technical trading strategies are profitable until the late 1990s but no longer profitable thereafter.
Model-based bootstrap	7	4	3	(1897-98)	
Reality check	0	1	1		
Genetic programming	2	1	3		• Overall, variable-moving average rules show the most reliable performance for the stock market over time.
Nonlinear	3	2	0		
Chart patterns	4	1	1		
Others	8	1	0		• For several non-US stock markets (e.g., Mexico, Taiwan, and Thailand), moving average rules generate substantial annual net profits of 10% to 30% until the mid-1990s.
Sub-total	26	12	10		
B. Foreign exchange markets					
Standard	8	2	3	5%-10%[c]	• For major foreign exchanges, a wide variety of technical trading strategies, such as moving averages, channels, filters, and genetically formulated trading rules, consistently generate economic profits until the early 1990s.
Model-based bootstrap	4	2	1	(1976-91)	
Reality check	1	0	0		
Genetic programming	3	0	1		• Several recent studies confirm the result, but also report that technical trading profits have declined or disappeared since the early 1990s, except for the yen market.
Nonlinear	3	0	0		
Chart patterns	2	1	2		
Others	3	1	1		
Sub-total	24	6	8		
C. Futures markets					
Standard	5	0	0	4%-6%[c]	• Technical trading strategies generate economic profits in futures markets from the late 1970s through the mid-1980s. In particular, technical trading strategies are consistently profitable in most currency futures markets, while they appear to be unprofitable in livestock futures markets.
Genetic programming	0	1	0	(1976-86)	
Non-linear	0	0	1		
Others	1	0	1		• Moving average and channel rules are the most consistently profitable strategies.
Sub-total	6	1	2		
Total	56	19	20		

[a] Studies on equity (index) futures and options and foreign exchange futures are categorized into 'stock markets' and 'foreign exchange markets' studies, respectively. 'Futures markets' studies include studies on other individual futures markets or various groups of futures markets.

[b] Gross returns. [c] Net of transactions costs.

Notes

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

[2] 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. This technique was not introduced to the West until the 1970s (Nison, 1991).

[3] In Smidt's survey an amateur trader is 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).

[4] According to Dimand and Ben-El-Mechaiekh (2005), a French researcher, Regnault, developed the first formal statement of the theory of efficient markets in 1863. Bachelier (1900) and Working (1949) also developed early versions of the theory.

[5] 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.

[6] A stop-loss order generates a sell signal whenever current price falls a fixed percentage below the initial price. A moving average rule generates a buy (sell) signal when a short moving average rises above (or falls below) a long moving average. A channel rule generates a buy (sell) signal anytime today's closing price is greater (lower) than the highest (lowest) price in a channel length. Momentum oscillator rules are various. The rule tested by Smidt (1965a) uses the average daily increase (decrease) in closing prices during the previous *n* days. If the value is greater (lower) than a given threshold value, a buy (sell) signal is generated. A relative strength rule measures price performance by comparing current price to an average of previous prices in relative terms.

[7] These returns are based on the total investment method in which total investment is 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.

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

[9] The nominal *p*-value is obtained by applying the bootstrap reality check methodology only to the best rule, thereby ignoring the effect of data snooping. Thus, it is a simple bootstrap *p*-value from the stationary bootstrap.

[10] Note that in Table 3 studies on equity (index) futures and options and foreign exchange futures are categorized into 'stock markets' and 'foreign exchange markets' studies, respectively. 'Futures markets' studies include studies on other individual futures markets or various groups of futures markets.

[11] By analyzing data on stock holdings of hedge fund managers, one of the most sophisticated investor groups, Brunnermeier and Nagel (2004) find that hedge funds 'rode' the technology bubble over the 1998-2000 period and reduced their holdings of technology stocks before prices collapsed. These findings are consistent with feedback models.

[12] The source for the data on CTA investment is The Barclay Group (http://www.barclaygrp.com/indices/cta/Money_Under_Management.html).

[13] This statement strictly applies only to studies that replicate 'old' results on 'new' data for the same market(s). Numerous studies provide a form of replication by applying successful technical trading rules from one market to

different markets over similar time periods. The independence of such results across studies is open to question because of the positive correlation of returns across many markets, i.e. U.S. and non-U.S. stock markets.

[14] The different views on technical analysis may stem partly from a reverse 'publication bias', which occurs when, '…a researcher who genuinely believes he or she has identified a method for predicting the market has little incentive to publish the method in an academic journal and would presumably be tempted to sell it to an investment bank' (Timmermann and Granger, p. 15). Publication bias, often called a 'file drawer' bias because the unpublished results are imagined to be tucked away in researchers' file drawer, occurs due to difficulty in publishing empirical studies that find insignificant results.