The Profitability of Technical Trading Rules in US Futures Markets: A Data Snooping Free Test

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Practitioners Abstract

Numerous empirical studies have investigated the profitability of technical trading rules in a wide variety of markets, and many of them found positive profits. Despite positive evidence about profitability and improvements in testing procedures, skepticism about technical trading profits remains widespread among academics mainly due to data snooping problems. This research tries to mitigate the problems by confirming the results of a previous study and then replicating the original testing procedure on new data. Results indicate that for various futures contracts and technical trading systems tested, technical trading profits have gradually declined over time. In general, substantial technical trading profits in the early 1980s are no longer available in the subsequent period.

Keywords: Technical Trading, Data Snooping, Replication, Market Efficiency, Trading Model, Futures Price Series, Transaction Costs, Benchmark

Introduction

Technical analysis is a forecasting method of price movements using past prices, volume, and open interest. Technical analysis includes a variety of forecasting techniques such as chart analysis, pattern recognition analysis, seasonality and cycle analysis, and computerized technical trading systems. Academic research on technical analysis is generally limited to techniques that can be easily expressed in mathematical forms, namely technical trading systems, although some recent studies attempt to test visual chart patterns using pattern recognition algorithms. Technical trading systems, as a variant of technical analysis, are designed to automatically recognize predictable trends in commodity prices under the expectation that the trends will continue in the future. A technical trading system consists of a set of trading rules that result from possible parameterizations and each rule generates trading signals (long, short, or out of market) based on their parameter values. Several popular technical trading systems are moving averages, channels, and momentum oscillators.

The profitability of technical trading rules has been a long-standing controversy. Numerous survey studies indicate that practitioners attribute a significant role to technical analysis. For example, futures fund managers rely heavily on computer-guided technical trading systems (Brorsen and Irwin), and about 30% to 40% of foreign exchange traders around the world believe that technical analysis is the major factor determining exchange rates in the short-run up to six months (e.g., Cheung and Wong). In contrast to the views of many practitioners, most academics are skeptical about technical analysis. Rather, they believe that markets are informationally efficient and hence all available information is impounded in current prices (Fama). In efficient markets, therefore, any attempts to make profits by exploiting currently available information are futile. In a famous passage, Samuelson argues that, "…there is no way of making an expected profit by extrapolating past changes in the futures price, by chart or any other esoteric devices of magic or mathematics. The market quotation already contains in itself all that can be known

about the future and in that sense has discounted future contingencies as much as is humanly possible" (p. 44).

Nevertheless, in recent decades rigorous theoretical explanations for the widespread use of technical analysis have been developed based on noisy rational expectation models (Brown and Jennings), behavioral (or feedback) models (De Long et al.), disequilibrium models (Beja and Goldman), herding models (Froot, Scharfstein, and Stein), agent-based models (Schmidt), and chaos theory (Clyde and Osler). For example, Brown and Jennings demonstrate that under a noisy rational expectations model in which current prices do not fully reveal private information (signals) because of noise (unobserved current supply of a risky asset) in the current equilibrium price, historical prices (i.e., technical analysis) together with current prices help traders make more precise inferences about past and present signals than do current prices alone.

In response to the ongoing debate, numerous empirical studies have investigated the profitability of technical trading rules in a wide variety of markets, and many of them found positive technical trading profits (e.g., Lukac, Brorsen, and Irwin; Brock, Lakonishok, and LeBaron; Chang and Osler). Such findings potentially represent a serious challenge to the efficient markets hypothesis.

Despite positive evidence about profitability and improvements in testing procedures, skepticism about technical trading profits remains widespread among academics. For example, in a recent and highly-regarded textbook on asset pricing, Cochrane argues that "Despite decades of dredging the data, and the popularity of media reports that purport to explain where markets are going, trading rules that reliably survive transactions costs and do not implicitly expose the investor to risk have not yet been reliably demonstrated" (p. 25). As the term "dredging the data" colorfully highlights, the skepticism appears to center on a major, and largely unresolved, problem in studies of technical analysis: data snooping. Data snooping occurs when a given set of data is used more than once for purposes of inference or model selection (White). If such data snooping occurs, any successful results may be spurious because they could be obtained just by chance with exaggerated significance levels (e.g., Denton; Lo and MacKinlay). In the technical trading literature, a fairly blatant form of data snooping is an ex post and "in-sample" search for profitable trading rules. More subtle forms of data snooping are suggested by Cooper and Gulen. Specifically, a set of data in technical trading research can be repeatedly used to search for profitable "families" of trading systems, markets, in-sample estimation periods, out-of-sample periods, and trading model assumptions including performance criteria and transaction costs. As an example, a researcher may deliberately investigate a number of in-sample optimization periods (or methods) on the same dataset to select one that provides the most favorable result. Even if a researcher selects only one in-sample period in an ad-hoc fashion, it is likely to be strongly affected by similar previous research. Moreover, if there are many researchers who choose one individual in-sample optimization method on the same dataset, they are collectively snooping the data. Collective data snooping is potentially even more dangerous because it is not easily recognized by each individual researcher (Denton).

As a method to deal with data snooping problems, a number of studies in the economics literature suggested simply replicating previous results on a new body of data (e.g., Lovell). It is interesting to note that Jensen emphasized this approach early on in the academic literature on

technical analysis, stating that "since it is extremely difficult to perform the standard types of statistical tests of significance on results of models like Levy's[1] (and indeed they would be invalid in the presence of possible selection bias anyway), we shall have to rely on the results of replications of the models on additional bodies of data and for other time periods." However, only one empirical work regarding technical trading followed this approach. Sullivan, Timmermann, and White replicated Brock, Lakonishok, and LeBaron's study for the subsequent 10 years (1987-96) of DJIA data and found that Brock, Lakonishok, and LeBaron's trading rules were not as successful during the subsequent period. That few technical trading studies have followed Jensen's suggestion may be due to difficulties in collecting sufficient new data or a lack of rigorous documentation about trading model assumptions and procedures. For a study to be a good candidate for replication, three conditions should be met. First, 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. Second, testing procedures must be carefully documented, so they can be "frozen" at the point in time the study was published. Third, the original work should be published long enough ago that a follow-up study can have a sufficient sample size. In the technical trading literature, Lukac, Brorsen, and Irwin's study provides such an excellent opportunity. They conducted comprehensive tests on a variety of US futures markets using a wide range of technical trading systems, trading rule optimization, and out-of-sample verification.

To determine whether technical trading rules have been truly profitable in US futures markets, this paper replicates Lukac, Brorsen, and Irwin's trading model on a new set of data. The original framework is replicated as closely as possible by keeping all the trading model assumptions in Lukac, Brorsen, and Irwin's work, such as trading systems, markets, in-sample optimization length, transaction costs, rollover dates, and other important assumptions. Hence, this study provides true out-of-sample tests for the profitability of technical trading rules in US futures markets. In this way, deleterious impacts of data snooping can be minimized, if not eliminated.

Trading Model

The trading model is a general procedure to process the input data and produce the required output by programming the technical trading systems and other relevant assumptions. The trading model typically consists of the input data, trading systems, performance measures, optimization method, and other important assumptions. In practice, the trading model can be applied to various futures markets with a few modifications for market-specific factors (e.g., daily trading limits). In general, the trading model is constructed to track several performance measures of the technical trading rules such as gross return, net return, or Sharpe ratio, and eventually provide optimized trading rules based on a specific performance criterion.

Input data

The trading model typically uses daily futures price series as the input data. Since future contracts have a limited life span, there are several possible ways to construct a data set to simulate the technical trading systems. Four basic types of price series are found in the previous

[1] Levy tested a large number of relative strength rules.

technical trading literature. The first approach is to consider only individual contracts. As an example, Peterson and Leuthold used the final 10 months of prices in each of 7 hog futures contracts (February, April, June, July, August, October, and December).

The second approach is to construct a continuous price series for the entire sample period by using one or two contracts (Taylor). For example, Taylor used December sugar futures contracts from 1974 to 1981 by taking the prices of the December 1974 contract from January 1974 to November 1974 inclusive, then the prices of the December 1975 contract from December 1974 to November 1975, and so on. However, since most futures contracts have meaningful liquidity only during a relatively short period (final three to five months before expiration) of their life spans, this method unavoidably includes a great deal of illiquid data and thus may produce spurious results in assessing the effectiveness of the technical trading rules (Gray and Nielsen).

The third approach is to develop a continuous price series by simply linking the contracts closest to expiration, i.e., the nearby contracts (Levich and Thomas; Szakmary and Mathur). Szakmary and Mathur explain this method as follows: "The contract nearest to delivery is used, except during the delivery month when the contract next nearest to delivery is utilized. The switch is made on the first day of the delivery month because, generally, trading volume is most active for the nearby contract only until very early in the delivery month. Trading activity then shifts to the contract next nearest to delivery" (p. 516). Another example is given by Dale and Workman, who stated that "The dominant contract, i.e., the one with the highest open interest, is used to obtain a price series that reflects the most important market characteristics. The price series in this study began with the March 1976 T-bill futures contract, which was used until the June 1976 contract became dominant, and June 1976 was used until the September 1976 contract became dominant, etc" (p. 82). The "dominant contract" can be regarded as the nearby contract with the rollover date around the first day of the delivery month of the current nearby contract because the next nearby contract usually has a higher open interest than the current nearby contract at that time. In fact, futures fund managers who heavily rely on the technical trading systems appeared to hold 80 percent of their position in the nearby contract because of liquidity costs (Brorsen and Irwin). Thus, this approach seems to well approximate the actual use of technical trading systems.

However, this third approach has two problems. The first problem arises when price differences between the old and new nearby contracts are large enough to create discontinuous breaks in the price series. For example, suppose that the closing price of a May corn futures contract is $2.50 per bushel on the rollover date and that the July corn futures contract closes at $2.00 per bushel on the same day. Also, suppose that on the next day the July corn futures price rises from $2.00 to $2.12, the daily allowable limit. The nearby contract price series will then provide the following closing levels for the two consecutive days: $2.50, $2.12. As a result, the nearby contract price series would imply a $0.38 loss on a day when a long position on the July corn contract would have realized a limit-up price gain of $0.12.

The second problem in using the linked nearby contract series is that the trading signals on the new nearby contract are taken from price movements of the old nearby contract for a period after the switch (rollover) between the two contracts. For example, if the 30-day moving average rule is applied to the new nearby contract, then for the first 29 days after the rollover date, the old nearby contract prices will be used to calculate the moving average. Thus, unless price

movements of the old and new contracts before the rollover date are completely matched or appropriately adjusted, the trading rule may generate a false signal.

The above problems can be solved using the last approach in which an existing position in the current nearby contract is closed out on a rollover date and a new position in the next nearby contract is simultaneously opened according to a trading signal generated by applying a given trading rule to past data of the new nearby contract (Lukac, Brorsen, and Irwin; Silber; Sullivan, Timmermann, and White). Therefore, transactions occur not only based on trading signals but also to rollover the current position. This method can avoid any distortion that arises from linking the old and new nearby contracts, although some arbitrariness in selecting the rollover date is inevitable. For trading purpose, the most popular choice of the rollover dates is the first notice day or an arbitrary day before the first notice day because several exchanges require extra margin in specific markets after the first notice day (Ma, Mercer, and Walker). In addition, since the open interest or the trading volume of a contract generally declines in the delivery month, problems associated with illiquid trading can be avoided with the earlier rollover date. It is known that price, volume, and open interest in the delivery month are often so volatile that the data can be meaningless.

Following Lukac, Brorsen, and Irwin, this study assumes that the current nearby contract rolls over the new nearby contract on the second Tuesday of the month preceding the delivery month of the current contract. This is consistent with the price series used by actual technical traders.

Performance Measures and Transaction Costs

Past studies of the futures market generally measured trading rule profits in dollar terms, although some studies reported percent returns to total investment. For example, Lukac, Brorsen, and Irwin employed the total investment method, in which total investment was composed of a 30% initial investment in margins plus 70% held back for potential margin calls. Thus, if a trader invested $10,000, then $3,000 would be used for initial margins and $7,000 for potential margin calls. If profits were $1,000 over a trading period, the percent return would be 10%.

Nevertheless, recent studies regarding the futures market use a holding period return or the continuously compounded (log) return per unit to assess trading profits. These return measures allow a direct comparison between futures trading returns and returns on alternative investments, because studies of the stock market or the foreign exchange market typically compute trading profits as percent returns per unit. Although defining a rate of return may be problematical in the futures market because there is no initial investment except for a margin account, Kho argued that “it provides a sufficient statistic for testing the profitability of trading rules because there exists a one-to-one correspondence between a daily price change and dollar gains” (p. 252). Then, the continuously compounded daily gross return on a technical trading rule j at time t can be calculated by

$$r_{jt}^{G} = [\ln(P_t) - \ln(P_{t-1})]S_{j,t-1}, \qquad (1)$$

where P_t is a futures price at time t and $S_{j,t-1}$ is an indicator variable that takes one of three values: +1 for a long position, 0 for a neutral position (i.e., out of the market), and -1 for a short position.

Jensen's definition of the efficient market hypothesis implies that a technical trading rule is profitable only if its risk-adjusted profits exceed transaction costs incurred from implementing trades. The net return provides such a measure of returns beyond transaction costs and risk under the assumption that all risk is diversifiable. Also, it can be used to compute risk-adjusted performance measures such as the Sharpe Index. Hence, this study uses net return as a performance measure to choose optimal trading rules during in-sample periods and evaluate their out-of-sample performance.[2] The net return per trade is calculated by subtracting an estimated transaction cost per trade from gross profits or losses per trade. The calculation includes every rollover trade. If a trader takes a position at time R and closes out the position at time $R+k$ based on a trading rule, then the net return from the single round-trip trade, with an estimated round-trip proportional transaction cost (c), is given by

$$r_{R,R+k} = \sum_{t=R+1}^{R+k} r_t^G + \ln(1-c). \tag{2}$$

The cumulative net return (r_j) for a trading rule j over the period from time R to time T can be calculated as follows:

$$r_j = \sum_{t=R+1}^{T} r_{jt}^G + n_j \ln(1-c). \tag{3}$$

where n_j is the number of round-trip trades generated by the trading rule j over the sample period from time R to time T. Obviously, transaction costs are an important factor that influences the net returns of trading rules.

Transaction costs generally consist of three components including the market maker's bid-ask spread, the broker's commission, and other transaction fees. The first part of transaction costs is the market maker's bid-ask spread.[3] In the futures markets, there exist two prices, a price at which a customer can buy (ask price or offer price) and a price at which a customer can sell (bid price). In order to earn a return, market makers sell at a higher price than they buy. If a customer deals with a market maker, then the customer buys for a high price and sells for a low price. The difference between the prices is referred to as the bid-ask spread, and sometimes is called execution cost, liquidity cost, or skid error. This bid-ask spread can be used as a proxy for the average round-trip cost for a non-member futures customer trading against market makers (Kuserk and Locke).

However, the formal bid-ask spread is not available because there are no official market makers in futures markets. Instead, the bid-ask spread is estimated in various ways. For example, Kuserk and Locke measured the representative scalper's mean daily realized bid-ask spreads, while Locke and Venkatesh estimated the implied effective bid-ask spread, which is defined as the difference between the average purchase price and the average sale price for all futures customers with prices weighted by transaction size. Table 1 presents previous estimation results for bid-ask spreads in futures markets. In brief, the spreads were nearly equal to the minimum price change (one tick) for each contract, although there were some deviations according to the estimation methods and sample periods. Technical trading studies in futures markets

[2] Description of an optimization method will be given in the next section.

[3] In the futures markets, scalpers are known to play the role of market makers.

incorporated this type of transaction costs into the general trading model by using such estimates of the bid-ask spread (e.g., Silber; Szakmary and Mathur), or by doubling the brokerage commission for each trade (Lukac, Brorsen, and Irwin; Lukac and Brorsen).

Another component of transaction costs is the brokerage commission. Since a broker executes the trade on behalf of a customer, he or she charges a commission as a compensation for order-processing costs. Szakmary and Mathur and Wang assumed a brokerage commission of $12.50 per contract (thus, $25 per round turn transaction), while Levich and Thomas estimated a much smaller brokerage commission of $11.00 per contract per round turn transaction. The other fees (total of approximately $2 per contract) such as the clearing fee, exchange fee, and brokerage fee are also imposed by the exchange to a non-exchange member to cover anticipated costs for providing the facility and environment to trade futures contracts (Wang, Yau, and Baptiste).

As a result, previous research on technical trading rules considered various transaction costs. Lukac, Brorsen, and Irwin and Lukac and Brorsen assumed transaction costs of $100 per contract per round-trip trade for commissions and liquidity costs across all futures markets tested. In particular, Lukac, Brorsen, and Irwin and Lukac and Brorsen employed transaction costs of $50 per contract per round-trip transaction to observe how different transaction costs affected trading profits. Taylor considered a conservative transaction cost of 0.2% per round-trip for currency futures contracts based on doubled bid-ask spreads and brokerage commissions. Silber used the bid-ask spread of each contract as transaction costs per round turn, and the spread was assumed equal to one tick for 12 markets, with crude oil and gold markets having a spread equal to two ticks. For currency futures markets, Levich and Thomas assumed transaction costs of 0.025% and 0.04% per transaction, and Szakmary and Mathur considered those of 0.1% per round-trip transaction. Finally, Wang used a bid-ask spread of $36 per contract plus a brokerage commission cost of $25 per round-trip transaction.

Following Lukac, Brorsen, and Irwin and Lukac and Brorsen, round-trip proportional transaction costs (c) corresponding to the dollar transaction costs of $100 per contract per round-trip trade will be used to compute net returns of technical trading rules. The dollar transaction costs per contract can be converted into percentage transaction costs per unit by dividing the dollar transaction costs by an average contract value, which can be in turn obtained from multiplying the number of units of a contract by an average of the buy and sell prices. However, since the average contract values differ according to a market considered, the corresponding proportional transaction costs are also different. For example, the corn futures market has average contract values around $10,000, while the T-bill futures market has around $1,000,000. If the average contract values for corn and T-bills during a trading period were $10,000 and $1,000,000, respectively, then the proportional transaction costs would be 1% (= 100/10,000) for corn and 0.01% (= 100/1,000,000) for T-bills. Thus, this study assumes four different proportional transaction costs per contract per round-trip trade: 0.2% for currencies, 0.5% for metals and agriculturals except for corn (1%), and 0.01% for T-bills. As long as average contract values exceed $50,000 for currencies and $20,000 for metals and agriculturals, both proportional transaction costs of 0.2% and 0.5% are greater than the dollar transaction costs of $100 per contract per round-trip transaction.[4] Indeed, when these dollar transaction costs are compared to

[4] The contract value of $50,000 results in an exact percentage transaction cost of 0.2% (=100/50,000). If the contract value is greater (less) than $50,000, percentage transaction costs are lower (higher) than 0.2%.

the sum of the bid-ask spreads and commissions estimated in other studies, the transaction cost of $100 per round-trip trade seems to be relatively conservative.[5]

Optimization; Out-of-Sample Verification; and Other Assumptions

Optimization refers to a method of determining the best parameter or parameter combination of a trading system based on a performance measure. According to the survey results by Brorsen and Irwin, most futures fund advisors selected parameters of their trading systems by optimizing over historical data, although there was little agreement about how much data to use to select the parameters.[6] Taylor, therefore, emphasized that the correct procedure to assess the profitability of technical trading is to choose the optimal parameter using the first part of the available data (optimization) and then evaluate the parameter upon the remaining data (out-of-sample verification), since traders can not guess the best trading rule ahead of time and it is unlikely an optimized rule will be optimal in the future. For example, Ready pointed out that an apparent success of moving average rules for the 1963-86 period in Brock, Lakonishock, and LeBaron was spurious, because their rules did not perform better than the fittest (optimal) trading rules formed by genetic programming over the pre-1963 period and hence they were not likely to be selected by traders at the end of 1962.

The out-of-sample verification is also an important factor in testing the performance of trading due to the danger of data snooping (or model selection) biases. If an optimal trading rule performed well on both in- and out-of-samples, then it is less likely that the trading rule was chosen by snooping data. On the other hand, Lukac and Brorsen found that for the channel system and the directional movement system various optimization strategies generated similar net portfolio returns. Hence, they concluded, "there appears to be little need for concern about how parameters are selected in academic studies as long as they are not based on in-sample returns" (p. 64).

This study, therefore, uses the same three-year re-optimization method as in Lukac, Brorsen, and Irwin without "snooping" for a well-performing optimization method. For each trading system and each market, the optimization method simulates trading using the past three-years of data over a wide range of parameters. The parameters showing the best performance over the three-year period are then used for the out-of-sample trading in the next year. At the end of the next year, new optimal parameters are selected, and this procedure is repeated during the rest of the sample period. For example, the optimal parameters of a trading system for 1993 are parameters that generate the highest mean net return from 1990 through 1992. The optimal parameters are then used for out-of-sample trading in 1993, and at the end of 1993 new optimal parameters for 1994 are selected using the data from 1991 through 1993, and so forth. This procedure ensures that all the technical trading systems are adaptive and all the trading results are out-of-sample.

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[5] By assuming a bid-ask spread of $12.50 per contract, a round-turn brokerage commission of $25 per contract, and a typical contract value of $60,000, Szakmary and Mathur estimated transaction costs of 0.06-0.07% per round-trip (37.5/60,000 = 0.063%). Assuming the same contract value of $60,000, the dollar transaction costs of $100 per contract deliver corresponding percentage transaction costs of 0.167%.

[6] About 30% of the advisors used historical data over five years, the smallest amount of data used was two years, and some used all the historical data they had available.

Several other important assumptions are included in the trading model. First, for the futures markets having daily trading limits, no position is taken or closed out when the high price equals the low price and both of these equal the closing price (lock-limit days), or when the contract's opening price is up or down the daily allowable limit. In practice, if futures prices reach their daily trading limit, little or no trading occurs since there are few or no sellers at a limit up move or buyers at a limit down move. Second, all trading is on a one contract basis, i.e., only one contract is used for each transaction. Third, no pyramiding of positions or reinvestments of profits is allowed. Finally, sufficient funds are assumed available to meet the margin requirement that may occur due to trading losses.

Technical Trading Systems

A technical trading system is composed of a set of trading rules that can be used to generate trading signals. In general, a simple trading system has one or two parameters that are used to vary the timing of trading signals. Trading rules contained in a system are the results of the parameterizations. For example, the Dual Moving Average Crossover system with two parameters (a short moving average and a long moving average) can produce hundreds of trading rules by altering combinations of the two parameters. Lukac, Brorsen, and Irwin simulated twelve representative technical trading systems that consist of moving averages, price channels, momentum oscillators, filters, and a combination system. Table 2 provides some general information about their twelve trading systems. The Directional Movement (DRM), Parabolic Time/Price (PAR), and Directional Parabolic (DRP) systems were introduced by Wilder, and all the other systems except Alexander's Filter Rule (ALX) and Wilder's three systems were presented by Barker. According to Lukac, Brorsen, and Irwin, each trading system was selected to be representative of the various types of systems that had been suggested by actual traders, previous studies and books. As noted previously, in this study, ten trading systems among the twelve trading systems are duplicated. The Parabolic Time/Price (PAR) and the Directional Parabolic (DRP) systems are excluded because despite the fact that returns generated by these systems tend to be extremely sensitive to a general trend and extreme points before the actual trading day, Lukac, Brorsen, and Irwin did not clearly specify how to decide them. In addition, several systems in both studies may not be identical in their mechanical structures because sufficient details were not provided by Lukac, Brorsen, and Irwin. The biggest difference may occur in the Outside Price Channel (CHL) system. Lukac, Brorsen, and Irwin tested a slightly different version of the CHL system from one in Barker's book, while this study follows Barker's original version since it seems more general and consistent. Alexander's Filter Rule (ALX) has a similar problem to that of the PAR and DRP systems because a trader has to decide a previous general trend before trading.

Moving average based trading systems are the simplest and most popular trend-following systems among practitioners. According to Neftci, the moving average method is one of the few technical trading procedures that are statistically well defined, because it generates trading signals by depending only on data available at the present time. Moving average systems take different forms depending on the method used to average past prices in the moving average calculations. For example, the simple moving average uses equal weighting on each past price considered, while the exponential moving average gives comparatively more weight to recent

prices. Their effect is to smooth out price actions, thereby avoiding false signals generated by erratic short-term price movements, and identifying the true underlying trend. A major problem associated with moving averages is that they do not perform well in congested markets and are subject to "whipsawing." This is particularly true of a moving average system that always keeps traders in the market and has no criteria for standing aside during periods of congestion. The problem of whipsawing, however, can be avoided by allowing a band surrounding the trend line (moving average) above and below. The Simple Moving Average with Percentage Price Band (MAB) system literally uses a simple moving average with a price band centered around it. A trading signal is triggered whenever the closing price breaks outside the band, and an exit signal is triggered when the price re-crosses the moving average. The upper and lower price bands act as a neutral zone that has the effect of keeping traders out of the market during non-trending conditions. By standing aside and not trading while prices are fluctuating within the price bands and the market is seeking a direction, traders may significantly increase the probability of profitable trades. The Dual Moving Average Crossover (DMC) system employs a similar logic to that of the Simple Moving Average with Percentage Price Band system by trying to find when the short-term trend rises above or below the long-term trend. The DMC system is a reversing system that is always in the market, either long or short. As market participants including brokers, money managers or advisers, and individual investors were known to extensively use the Dual Moving Average Crossover system, many academics have tested this system since the early 1990s.[7]

Next to moving averages, price channels are also extensively used technical trading methods. The price channel is sometimes referred to as "trading range breakout" or "support and resistance." The fundamental characteristic underlying price channel systems is that market movement to a new high or low suggests a continued trend in the direction established. Thus, all the price channels generate trading signals based on a comparison between today's price level with price levels of some specified number of days in the past. The Outside Price Channel (CHL) system is analogous to a trading system introduced by Donchian, who used only two preceding calendar week's ranges as a channel length. This system generates a buy signal anytime the closing price is outside (greater than) the highest price in a channel length (specified time interval), and generates a sell signal anytime the closing price breaks outside (lower than) the lowest price in the price channel. The CHL system is reversing and always in the market, either long or short. The L-S-O Price Channel (LSO) system is another type of price channel. Most price channel methods are reversing systems – always in the market, either long or short. However, the LSO system can be long, short, or out of the market. In the LSO system, today's closing price is compared to the price action of a cluster of consecutive days some time in the past. The cluster of days is termed the Reference Interval (RI). The M-II Price Channel (MII) system is yet another variant of technical trading systems based on the price channel. This system is a reversing system that is always in the market. Long or short positions are established and maintained by comparing today's close with the theoretical high or low of the first day of the price channel. For example, if today's close is above the Reference Day Theoretical High (RDTH), a long position is established on the close and is maintained until the market moves below the Reference Day Theoretical Low (RDTL) at which time the long position is liquidated and a short position is simultaneously established – offset and reverse (OAR).

[7] For more details about these technical trading systems, see the original references (Barker; Wilder) or Lukac, Brorsen, and Irwin's work.

Momentum oscillator techniques derive their name from the fact that trading signals are obtained from values which “oscillate” above and below a neutral point, usually given a zero value. The basic concept of momentum oscillators is to detect trends by quantifying the magnitude of price changes, compared to the absolute price levels on which the price channels based. “By looking at the net increase in prices over the number of days designated by an n-day momentum indicator, intermediate fluctuations are ignored, and the pattern in price trend can be seen. The longer the span between the observed points, the smoother the results” (Kaufman, p. 130). The momentum values are very similar to standard moving averages, in that they can be regarded as smoothed price movements. However, since the momentum values generally decrease before a reverse in trend has taken place, momentum oscillators may identify a change in trend in advance, while moving averages usually cannot. Oscillators are generally known as being used in conjunction with other trading systems. The Directional Indicator (DRI) system is a prominent example of momentum oscillators. Since the directional indicator is sensitive to changes in market volatility, it clearly and precisely defines congestion, despite its relative simplicity (Barker). A trending period can be characterized as one having a significant excess of either up or down movement. This system generates trading signals based on the excess. The Range Quotient (RNQ) system is also a member of the momentum oscillators, but is quite different from any other oscillator systems in that it can contain more information about recent price patterns in a single number, i.e., Range Quotient. This system is based on the relationship between the average daily price range and the total price range over some time interval. According to Barker, simple (unsmoothed) technical trading systems often provide superior performance to their exponentially smoothed counterparts. One problem with unsmoothed methods is that data being discarded has as significant an impact on the results as today’s price data. However, the RNQ system, without a smoothing process, virtually eliminates this problem as the discarded data can never increase the total price range. The Reference Deviation (REF) system is another oscillator-type system that uses a moving average as a reference point. This system is analogous to other oscillator methods in the sense that buy and sell signals are generated by comparing the reference index with arbitrary fixed threshold levels. The Directional Movement (DRM) system is an oscillator-type technical trading system designed by Wilder. The objective of this system is to determine whether a market is likely to experience a trending or trading range environment. A trending market will be better signaled by the adoption of trend-following indicators such as moving averages, whereas a trading range environment is more suitable for oscillators (Pring). The Directional Movement measures the relative strength of a market over a fixed time period. It produces two directional indicators ranging from 0 to 100%, and buy or sell signals are generated by comparing the two indicators.

Filter systems “filter” out smaller price movements by constructing trailing stops for price movements above or beneath the current trend and generating buy or sell signals only on the larger price changes. The trailing stops have various forms such as some predetermined amount of past extreme prices (Alexander’s Filter Rule) or particular weighted averages of past prices (Parabolic Time/Price system). Alexander’s Filter Rule (ALX) was first introduced by Alexander and exhaustively tested by numerous academics until the early 1990s. Since then, however, its popularity among academics has been replaced by moving average methods. This system generates a buy (sell) signal when today’s closing price rises (falls) by x% above (below) its most recent low (high).

Benchmark Strategies

Technical trading returns in a market are often compared with returns to a benchmark strategy in order to test the efficient market hypothesis. Two benchmarks frequently used in previous technical trading research are returns to a buy-and-hold strategy and zero mean profits.[8] In particular, the buy-and-hold strategy has long been used as the benchmark regardless of markets studied. As the name indicates, traders who follow the buy-and-hold strategy buy an asset at the beginning of a trading period, hold it during the period, and sell it on the final day of the period. The buy-and-hold strategy may be implemented by a naïve trader who has no information but simply believes that price of an asset will ultimately increase over time. The naïve strategy will capture any overall up-trend in the market. The validity of the buy-and-hold strategy as the benchmark comes from the sub-martingale model in which expected returns conditional on information in past prices are nonnegative. This implies that "If the market correctly uses available information and if it sets prices so that expected returns are positive, then the best trading rule for any security is to buy and hold. If the market is efficient, then the buy-and-hold strategy has higher expected returns or profits than any strategies that involve periods when the security is not held or, like the filter rules, involve periods when the security is sold short" (Fama, p. 141). On the other hand, technical analysts believe that there are periods when true expected returns are negative because the market does not correctly use available information. In this case, technical trading rules may generate higher expected returns than the buy-and-hold strategy.

However, several researchers have questioned whether the buy-and-hold strategy could be generally applied to futures markets as a benchmark, because the stock and the futures markets have different market structures. Leuthold pointed out that the buy-and-hold strategy may not be a reasonable benchmark for futures markets, because "(1) contracts are generally only for a duration of about one year as opposed to several years for securities on the stock exchange, so no long-run trends due to inflation exist; (2) for every long position on the commodities market, there is a short position, a situation not true for the stock market; (3) there is no a priori reason on the commodities market to initially buy-and-hold, as opposed to sell-and-hold" (p. 886). Neely, Weller, and Dittmar also argued that the buy-and-hold strategy may be inappropriate as a benchmark for the foreign exchange market since there was no general long-run trend observed in the market. In fact, the same is true for futures markets.

Peterson and Leuthold, thus, argued that zero mean profits should be the benchmark for futures markets due to the following reasons: (1) regular dividend payments in the stock market represent the equilibrium expected profits or returns, while share price increases become the excess returns (Fama). However, because futures contracts have no guaranteed return, there is nothing analogous to a dividend payment. The equilibrium expected profits or returns are, therefore, zero; (2) unlike the stock market, the futures market is a zero-sum game in which there are an equal number of longs and shorts, so that gains for one side are equal to losses for the other side. Lukac and Brorsen also argued that the zero mean profits could serve as the benchmark even after taking risk into account. They found that in some previous works (e.g., Lukac, Brorsen, and Irwin) technical trading returns were either uncorrelated or had a small

[8] Returns from a buy-and-hold strategy are sometimes referred to as unconditional returns because they are not conditioned on trading signals.

negative correlation with returns on stocks and bonds. If this is generally true, then the expected returns of technical trading rules are equal to the risk-free rate in the Capital Asset Pricing Model (CAPM). Because margin requirements can be posted in Treasury bills in futures markets, no capital is needed to finance a position. "Therefore a test of whether returns are zero is equivalent to a test that considers risk" (p. 601). In the light of these arguments, the zero mean profits seem to be an appropriate benchmark for futures markets. Hence, this study adopts the zero mean profits as the benchmark.

Risk-adjusted Performance Measure

Although most technical trading studies for futures markets found that technical trading rules have no systematic risk, the results were ex post and might vary according to different sample periods. Thus, the zero mean profit as a benchmark may be insufficient to take account of risk. Similarly, the buy-and-hold strategy cannot be either a necessary or a sufficient condition to judge whether technical trading returns are just a reward for risk, because the trading rules often take neutral positions (i.e., out of market) and therefore may bear much less risk than the buy-and-hold strategy. Several techniques have been used in the technical trading literature to explicitly measure the risk-adjusted performance of trading rules. One of the popular risk-adjusted performance measures is the Sharpe Index that accounts for the excess return per unit of total risk. The Sharpe Index, which is derived from the capital market line, is calculated by dividing the excess return for the portfolio *j* by its standard deviation, $\sigma(r_j)$:

$$S_j = \frac{E(r_j) - r_F}{\sigma(r_j)}, \tag{4}$$

where $E(r_j)$ is the expected return on any portfolio (or asset) j and r_F is the risk-free rate of interest. The ex post measure of the Sharpe Index can be estimated by

$$\hat{S}_j = \frac{\bar{r}_j - \bar{r}_F}{\hat{\sigma}_j}, \tag{5}$$

where $\bar{r}_j$ indicates the mean return to the portfolio j and $\bar{r}_F$ indicates the mean return to a risk-free asset. In futures markets, since futures traders can deposit Treasury bills for margin requirement, there is no need to sacrifice the risk-free return in order to take part in an alternative investment. Thus, the Sharpe Index of a trading rule *j* can be measured by

$$\hat{S}_j = \bar{r}_j / \hat{\sigma}_j, \tag{6}$$

where $\bar{r}_j$ indicates the annualized mean net return during the sample period and $\hat{\sigma}_j = \sqrt{\sum_{t=1}^{N} (r_{jt} - \bar{r}_j)^2 / (N-1)}$.

There are some limitations with respect to the Sharpe Index. First, if the variance of returns is close to zero, this makes the Sharpe Index numerically unstable at extremely large values. Second, because the standard deviation of returns represents its total variability, the Sharpe Index penalizes the variability of profitable returns, which is usually unimportant to traders, exactly the same as the variability of losses that is traders' major concern. Third, the Sharpe Index cannot distinguish the clustering of profits and losses because it is independent of the order of various data points. Even if two trading rules have the same Sharpe Index, one rule that has an even

mixture of profits and losses is usually preferred to another rule that has clusters of losses and clusters of profits (Dacorogna et al.). In spite of these shortcomings, the Sharpe Index has been used in numerous technical trading studies as a risk-adjusted performance measure or a model selection criterion (e.g., Silber; Neely, Weller, and Dittmar: Sullivan, Timmermann, and White; and others). Hence, this study uses the Sharpe Index expressed by (6) as a risk-adjusted performance measure.

Statistical Tests

The most widely used method to test the statistical significance of technical trading profits is to use the Z-statistic or the t-statistic. Let Y_1 and Y_0 be independent and normally distributed random variables representing returns from a technical trading rule and a benchmark strategy, respectively. Since we are interested in testing whether technical trading returns outperform benchmark returns, the null hypothesis $H_0 : \bar{Y}_1 - \bar{Y}_0 = 0$ can be tested against $H_1 : \bar{Y}_1 - \bar{Y}_0 > 0.$ If the variances are unknown and the sample sizes are large, the test statistic is given by

$$Z = \frac{\bar{Y}_1 - \bar{Y}_0}{\sqrt{(S_1^2 / N_1) + (S_0^2 / N_0)}}, \tag{7}$$

where $\bar{Y}_1$ and S_1^2 are the sample mean and variance of returns from a technical trading rule, $\bar{Y}_0$ and S_0^2 are the corresponding statistics from the benchmark, and N_1 and N_0 are the number of observations for each trading strategy. The Z-statistic has a standard normal distribution when H_0 is true. When a benchmark is "zero mean profits," the Z-statistic may be valid because technical trading rules and the benchmark are independent.

However, sometimes technical trading rules and a benchmark strategy may be closely related and thus Y_1 and Y_0 are likely to be dependent. For example, trend-following trading rules are positively (negatively) correlated to a buy-and-hold strategy in up- (down-) markets. In these cases, thus, a paired test can be more appropriate. Let $D_i = Y_{1,i} - Y_{0,i}$, $i = 1,2,\ldots,N.$ Suppose that $D_1, D_2, \ldots, D_N$ are random samples from $N(\mu_D, \sigma_D^2),$ where μ_D and σ_D^2 are the mean and variance of the differences. Then, the null hypothesis $H_0 : \mu_D = 0$ can be tested by a test statistic

$$T = \frac{\bar{D}}{S_D / \sqrt{N}}, \tag{8}$$

where $\bar{D}$ and S_D are the sample mean and sample standard deviation of the *N* differences. The statistic *T* has a t-distribution with $N - 1$ degrees of freedom. A potential problem of the standard statistics arises from the fact that a sequence of returns from each trading strategy or their differences is assumed to have normal distributions. In general, the distribution of technical trading returns is unknown or may change over time (Taylor). Moreover, Lukac and Brorsen found that technical trading returns in the individual futures markets were positively skewed and leptokurtic. They argued that "the market level returns do not seem normal, and thus past research that used t-tests on single commodity returns may be biased" (p. 603).

When the underlying distribution of observations is not known, an alternative approach to parametric tests based on t- or Z-statistic is the bootstrap methodology introduced by Efron. The

idea of the bootstrap methodology is to use a single available data set "to design a sort of Monte Carlo experiment in which the data themselves are used to approximate the distribution of the error terms or other random quantities in the model" (Davidson and MacKinnon, p. 763). In the technical trading literature, several types of bootstrap procedures have been used to obtain significance levels for trading rule profits or as a test for model specification. In this study, however, statistical tests are conducted by estimating t-statistic in terms of the equation (8), and the bootstrap methods will be used in future work.

Data

Lukac, Brorsen, and Irwin investigated twelve futures markets over the 1975-1984 period.[9] The twelve futures markets include highly traded agricultural commodities, metals, and financials. In this study, daily price series of eight markets among the twelve futures markets are analyzed over the 1975-2002 period. They are corn, soybeans, live cattle, pork bellies, lumber, British pound, Deutsche mark, and T-bill contracts. The rest of four futures markets are not tested because of the lack of daily price limit data which may seriously influence on trading returns. In a future study, they may be included in analysis with the limit data. Daily price data for each market from 1975 through 2002 are used to evaluate in- and out-of-sample performances of technical trading rules, with the exception of the three financials (pound, mark, and T-bills) that have slightly shorter sample periods. In order to assess the performance of trading rules on a new set of data, we divide the full out-of-sample period (1978-2002) into two subperiods: 1978-1984 and 1985-2002. The first subperiod is the same sample period that Lukac, Brorsen, and Irwin tested. Table 3 presents a detailed description (specific markets, exchanges, and in- and out-of-sample periods) of the data.

Results

Across the eight futures markets, nine trading systems are duplicated and simulated over the same sample period (1975-1984 for agriculturals and 1977-1984 for financials) as tested by Lukac, Brorsen, and Irwin. In each out-of-sample year, annual net returns of optimal trading rules for each trading system are compared to Lukac, Brorsen, and Irwin's.[10] Table 4 provides the summary statistics of confirmation results.[11] Correlation coefficients between returns from two studies range from 0.14 (for ALX) to 0.60 (for DMC) with an average correlation coefficient of 0.49. In about 72% of all cases, signs of returns appear to be consistent with Lukac, Brorsen, and Irwin's. Some inconsistent results may be caused by various reasons. As described above, Lukac, Brorsen, and Irwin used a slightly different version of the CHL system from that in

[9] Their out-of-sample period begins in 1978 since three years from 1975 through 1977 are used to optimize trading rules.

[10] The L-S-O price channel system, in addition to the two parabolic related systems, is not simulated in the confirmation part because Lukac, Brorsen, and Irwin misspecified values of the second parameter (reference interval), which must not exceed values of the first parameter (price channel).

[11] Tomek distinguishes between "confirmation" (or "duplication") and "replication." He uses "confirmation" to mean attempts to fit the original model with the original data and "replication" to fit the original specification to new data (p. 6).

Barker, while this study employs Barker's original version. Results for Alexander's filter rules (ALX) may also differ because the initial trend in the system is determined arbitrarily by traders. The DRM system may produce different returns, depending on how to set the initial entry point into trading. On the other hand, the continuously compound returns used in this study have slight downward (upward) biases against Lukac, Brorsen, and Irwin's positive (negative) returns that were calculated by using the total investment method. Moreover, even a small amount of difference in transaction costs may result in different optimal parameters, which in turn influence on trading returns. In fact, the round-trip proportional transaction costs used in this study tend to be slightly higher than the dollar transaction costs used by Lukac, Brorsen, and Irwin. Several other sources, such as programming errors, clerical errors, and differences in data (original prices and daily price limits), may also cause different results. Nevertheless, the results shown in Table 4 suggest that the general trading model used in this study duplicates Lukac, Brorsen, and Irwin's model reasonably well.

Tables 5, 6, and 7 report the performance of optimal trading rules for each sample period. As shown in Table 5, during the first out-of-sample period (1978-1984 for agriculturals, 1980-84 for financials) five out of the eight commodities show economically and statistically significant returns from at least three or more trading systems. Specifically, significant returns are found in corn by three (LSO, MII, and DRI) out of the ten systems, lumber by four systems (DMC, LSO, MII, and RNQ), British pound by three systems (MAB, DMC, and DRI), Deutsche mark by seven systems (MAB, DMC, LSO, MII, DRI, RNQ, and REF), and T-bills by four systems (MAB, DMC, LSO, and ALX). Eight out of the ten trading systems, except the CHL and DRM systems, generate significant profits in one or more commodities and their annual mean net returns range from 2.63% for T-bills to 24.12% for Lumber, while the corresponding Sharpe ratios range 0.48-1.51. These Sharpe ratios compare with those in the range of around 0.3-0.4 for investing (buying and holding) in aggregate US stock portfolio (LeBaron). One interesting point to note is that although for the profitable trading systems annual mean net returns of T-bills are much lower than those of other contracts, their Sharpe ratios are as large as those of other contracts, or even higher. For example, the LSO system produces an annual mean net return of 24.12% in lumber with a Sharpe ratio of 1.02, while the same system generates an annual mean net return of 4.65% in T-bills with a Sharpe ratio of 1.51. This implies that T-bill returns were much less volatile than those of other contracts during the sample period. On the other hand, these successful results in the earlier period are consistent with what Lukac, Brorsen, and Irwin found for the same sample period, providing further confirmation.

Table 6 presents the replication results with annual mean net returns and relevant Sharpe ratios for the new set of data from 1985 through 2002. Over the later out-of-sample period, the profitability of technical trading rules declines sharply across most futures contracts tested. Only two trading systems (LSO and ALX) consistently yield statistically significant returns in two markets (lumber and T-bills), with largely reduced annual mean net returns compared to those of the earlier sample period (1978-1984). The LSO system generates an annual mean net return of 13.46% in lumber and 1.38% in T-bills, respectively, and the ALX system generates 0.63% in T-bills. In corn, British pound, and Deutsche mark markets in which three or more trading systems realized statistically significant trading profits during the earlier sample period, no significant trading profits are found. Therefore, the earlier successful results do not seem to persist in the later period.

The results for the entire out-of-sample period (1978-2002) are presented in Table 7. As shown in the table, profit levels and the number of profitable markets and trading systems largely decrease compared to those of the earlier sample period (1978-1984). Three (lumber, Deutsche mark, and T-bills) out of the eight commodities indicate statistically significant returns. However, lumber futures indicate significant returns only in one (LSO) of the ten trading systems, Deutsche mark in two systems (LSO and REF), and T-bills in four systems. Among the ten trading systems, the LSO price channel system appears to be the most profitable strategy with annual mean net returns of 16.44% for lumber, 4.43% for Deutsche mark, and 2.34% for T-bills. The corresponding Sharpe ratios of the LSO system are 0.71, 0.54, and 1.29, respectively. The moving average systems (MAB and DMC) and Alexander's filter rules (ALX) produce annual mean net returns of around 1% only for T-bills with Sharpe rations of around 0.5, and the REF system generates an annual mean net return of 4.33% for Deutsche mark with a Sharpe ratio of 0.39. Therefore, the results in Table 7 seem to reflect those shown in Tables 5 and 6, that is, the successful performance of technical trading rules in the earlier subperiod and the poor performance in the later subperiod.

Figures 1-19 vividly illustrate the above results. First, Figures 1-8 show how equally weighted annual mean net returns across all the ten trading systems have been changed in each futures market over the entire out-of-sample period. As shown in these figures, in most contracts the annual mean net returns generally decline over time. Each figure includes a regression equation that is estimated as:

$$y_t = \alpha + \beta x + \varepsilon_t, \tag{9}$$

where α is the intercept parameter, β is a parameter that is used to test whether the change in annual net returns over time is statistically significant, y_t is annual net returns across all the ten trading systems, x is a time trend, and ε_t is an error term. Results for the equation (9) indicate that the β coefficient is negative in six of the eight markets and it is statistically significant in four markets. For example, for corn and Deutsche mark, the estimates of the regression equation (9) are:

$$y_t = \underset{(0.77)}{3.3461} - \underset{(-2.01)}{0.5873}x,$$

$$y_t = \underset{(3.97)}{7.8802} - \underset{(-3.39)}{0.5901}x,$$

respectively, and the terms in parentheses indicate the standard t-statistics. These results imply that in both markets annual mean net returns across all the technical trading systems begin at 3.35% and 7.88% in 1978 and 1980, respectively, and decline by around 0.59% in each year. Although the β coefficient shows positive values for two markets (live cattle and pork bellies), it is not much different from zero with insignificant t-statistics. Therefore, it appears that technical trading profits in most futures markets considered have gradually declined over time. Similar results are found in Figures 9-18, which illustrate that how equally unit-weighted annual mean net returns across all the eight futures markets have been changed by each trading system over the entire out-of-sample period. The simple regression results indicate that for nine of all the ten trading systems the β coefficient is negative. For five of the nine trading systems, the β coefficients are statistically significant and three are marginally significant. Although β for the REF system has a positive value, it is close to zero with an insignificant t-statistic. Finally,

Figure 19 shows changes in aggregate portfolio annual mean net returns across all the markets and trading systems over time. The regression coefficients for the equation (9) are estimated as:

$$y_t = \underset{(0.39)}{0.8217} - \underset{(-1.69)}{0.2383}x,$$

and imply that the aggregate portfolio trading profits steadily declined over the entire out-of-sample period.

Summary and Conclusions

Numerous previous empirical studies regarding technical analysis found that technical trading strategies were profitable in a variety of speculative markets. However, most academics are skeptical about the positive evidence mainly due to data snooping problems. In the technical trading literature, data snooping practices appear to be widespread because researchers have a strong tendency to search for profitable "families" of trading systems, markets, and trading model assumptions. As suggested by many economics studies, this study tried to solve the problem by duplicating the original procedures and then replicating them on a new set of data.

The confirmation results indicated that the trading model developed in this study well approximates the original procedure, with a few exceptions. During the earlier out-of-sample period (1978-1984), several technical trading systems produced statistically significant economic profits in corn, lumber, British pound, Deutsche mark, and T-bill contracts. This finding is consistent with that identified in Lukac, Brorsen, and Irwin's original study. However, the replication results on new data were somewhat disappointing. Only two (the LSO price channel system and Alexander's filter rules) of the ten trading systems continue to generate statistically significant profits in lumber and T-bill contracts. In fact, it appeared that for most contracts and trading systems tested, technical trading profits gradually declined over time. The substantial trading profits in the earlier period were no longer available in the subsequent period, with a few exceptions. In their recent work, Kidd and Brorsen reported that returns to the managed futures funds and Commodity Trading Advisors (CTAs), which predominantly use technical analysis, have declined dramatically in the 1990s, and that such reduction of technical trading profits could be caused by structural changes in markets, such as "a decrease in price volatility and an increase in large price changes occurring while markets are closed" (p. 7).

On the other hand, it is still unclear that the apparent earlier success of some technical trading systems is a result of whether temporal inefficiency of futures markets or data snooping, because a few trading systems (LSO and ALX) continued to produce relatively small but statistically significant profits in specific markets (lumber and T-bills). This issue will be more rigorously investigated in future research with advanced statistical procedures such as White's Reality Check Bootstrap methodology.

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Table 1. Previous Estimation Results of the Bid-Ask Spread in Futures Markets.

Studies	Markets[a]	Data	Estimation Methods and Results
Thompson and Waller (1987)	Coffee and cocoa futures contracts in the CSCE	Transaction-to-transaction prices from 1981-83	Execution costs were estimated by the average of the absolute value of observed price changes. The average estimated execution costs per contract were $12.60 for near cocoa contracts and $32.25 for near coffee contracts.
Brorsen (1989)	Corn futures contracts in the CBT	Intraday prices of 6 different contracts traded from 1983-84	The liquidity costs, which were estimated by Thompson and Waller's (1987) method, were approximately equal to the minimum price changes of $12.50 per contract.
Kuserk and Locke (1993)	12 commodity futures contracts in the CME	The Computerized Trade Reconstruction (CTR) records from the CME for 7/90-9/90	The representative scalper's mean daily realized bid-ask spreads were measured. Currency and interest rate products appeared to have lower spreads, while agricultural futures had relatively high spreads: in dollar term, British pound: 6.16 (12.5), Canadian dollars: 7.34 (10), Deutsche mark: 5.62 (12.5), Swiss franc: 7.66 (12.5), Japanese yen: 7.53 (12.5), Eurodollar: 8.14 (25), T-Bills: 14.37 (25), S&P 500: 19.03 (25), Live cattle: 4.44 (10), Live hogs: 12.44 (10), Pork bellies: 11.89 (10), and Feeder cattle: 21.24 (11).[b]
Fleming, Ostdiek, and Whaley (1996)	S&P 500 futures contracts in the CME	Intraday prices from the CME time and sales file in March 1991	The bid-ask spread was inferred using Smith and Whaley's (1994) method of moments spread estimator. For the nearby futures contract, the effective bid-ask spread was $0.0558 per unit, only slightly higher than the minimum tick size ($0.05, or $25.00 per contract).
Locke and Venkatesh (1997)	12 commodity futures contracts in the CME	The trade register data for nearby futures contracts from 1/1/92-6/30/92	Estimated was the difference between the average purchase price and the average sale price for all futures customers with prices weighted by transaction size. The results were: Live hog: 7.30 (10), Pork bellies: 10.32 (10), Live cattle: 3.07 (10), Lumber: 15.92 (16), Feeder cattle: 9.42 (11), Canadian dollar: 6.05 (10), Swiss franc: 20.89 (12.5), Deutsche mark: 14.28 (12.5), Pound sterling: 18.12 (12.5), Japanese yen: 17.47 (12.5), Eurodollars: 4.81 (25), S&P 500: 16.58 (25).
Ferguson and Mann (2001)	14 commodity futures contracts in the CME	The Computerized Trade Reconstruction (CTR) records from the CME for 1/92-6/92	Two different customer execution spreads (the mean customer buy price less the mean customer sell price for 5-minute intervals) were estimated. One is for all customer trades and the other is against market makers. The execution spread against market makers were: S&P 500: 7.00 (25), Mark: 5.92 (12.5), Swiss franc: 8.08 (12.5), Pound: 7.24 (12.5), Yen: 6.32 (12.5), Canadian dollar: 7.28 (10), Eurodollar: 3.81 (25), T-bill: 9.39 (25), LIBOR: 3.40 (25), Live cattle: 3.65 (10), Pork bellies: 11.60 (10), Hogs: 7.26 (10), Feeder cattle: 12.50 (10), Lumber: 25.55 (16).

[a] CSCE: New York Coffee, Sugar, and Cocoa Exchange.
CBOT: Chicago Board of Trade.
CME: Chicago Mercantile Exchange.

[b] Numbers in parentheses refer to minimum tick sizes for each futures contract.

Table 2. Lukac, Brorsen, and Irwin's Trading Systems Categorized by System Type, Number of Parameters, and Time of Trading.

Trading Systems	System Type	Number of Parameters	Time of Trading[a]
Simple Moving Average with Percentage Price Band (MAB)	Moving average	2	Open
Dual Moving Average Crossover (DMC)	Moving average	2	Open
Outside Price Channel (CHL)	Price channel	1	Close
L-S-O Price Channel (LSO)	Price channel	2	Close/Stop
M-II Price Channel (MII)	Price channel	1	Close
Directional Indicator (DRI)	Momentum oscillator	2	Open
Range Quotient (RNQ)	Momentum oscillator	2	Open
Reference Deviation (REF)	Momentum oscillator	2	Open
Directional Movement (DRM)	Momentum oscillator	1	Stop
Alexander's Filter Rule (ALX)	Filter	1	Close
Parabolic Time/Price (PAR)	Filter	1	Stop
Directional Parabolic (DRP)	Combination system	2	Stop

[a] This column indicates when trades are made: Open (Close) denotes that a trade based on today's trading signal is made at tomorrow's opening (today's closing) price; Stop indicates that a stop order was assumed to be given to a broker and the order exercised at the stop price; Close/Stop indicates that every market entrance (exit) is made at today's closing price (stop).

Table 3. Descriptions of Futures Price Series.

Commodity	Exchange[a]	In-Sample (Out-of-Sample) Period
Corn	CBOT	1/1975-12/2001 (1/1978-12/2002)
Soybeans	CBOT	1/1975-12/2001 (1/1978-12/2002)
Live Cattle	CME	1/1975-12/2001 (1/1978-12/2002)
Pork Bellies	CME	1/1975-12/2001 (1/1978-12/2002)
Lumber	CME	1/1975-12/2001 (1/1978-12/2002)
British Pound	IMM	1/1977-12/2001 (1/1980-12/2002)
Deutsch Mark	IMM	1/1977-12/1997 (1/1980-12/1998)
U.S. Treasury Bills (13 weeks)	IMM	1/1977-12/1995 (1/1980-12/1996)

[a]CBOT: Chicago Board of Trade.

CME: Chicago Mercantile Exchange.

IMM: International Monetary Market in Chicago Mercantile Exchange.

Table 4. Summary Statistics of Confirmation Results, 1978-1984.

Trading System[a]	Correlation Coefficient	Sign Consistency (%)
MAB	0.49	64
DMC	0.60	78
CHL	0.53	72
MII	0.48	92
DRI	0.40	72
RNQ	0.53	70
REF	0.55	70
DRM	0.14	60
ALX	0.24	72
Average	0.49	72

[a]MAB: Simple Moving Average with % Price Band DMC: Dual Moving Average Crossover CHL: Outside Price Channel
MII: M-II Price Channel DRI: Directional Indicator RNQ: Range Quotient
REF: Reference Deviation DRM: Directional Movement ALX: Alexander's Filter Rule

Table 5. Annual Mean Net Returns for Ten Trading Systems, 1978-1984.[a]

Contract		Trading System[b]										
		MAB	DMC	CHL	LSO	MII	DRI	RNQ	REF	DRM	ALX	Average
Corn	AR*100[c]	3.28	4.76	3.07	8.27*	8.18*	8.85**	6.43	4.06	-4.89	0.17	4.22
	Sharpe ratio	0.22	0.29	0.21	0.55	0.48	0.63	0.43	0.25	-0.30	0.01	0.28
Live Cattle	AR*100	-4.98	-10.11	-2.31	4.31	-8.46	-1.38	-8.19	-9.09	-10.11	-6.11	-5.64
	Sharpe ratio	-0.32	-0.55	-0.13	0.28	-0.46	-0.11	-0.46	-0.53	-0.58	-0.40	-0.32
Pork Bellies	AR*100	-13.35	2.08	-17.36	2.03	-14.66	-0.34	-7.10	-22.88	-8.00	3.88	-7.57
	Sharpe ratio	-0.44	0.06	-0.55	0.06	-0.41	-0.01	-0.21	-0.69	-0.24	0.11	-0.23
Lumber	AR*100	6.45	23.40***	5.53	24.12***	15.09**	4.18	14.47**	5.78	4.33	-13.21	9.01
	Sharpe ratio	0.31	0.91	0.25	1.02	0.59	0.23	0.58	0.24	0.19	-0.63	0.37
Soybeans	AR*100	1.80	4.92	-4.13	5.15	0.46	-0.49	-3.65	-0.92	1.51	-6.79	-0.21
	Sharpe ratio	0.09	0.21	-0.20	0.23	0.02	-0.03	-0.17	-0.04	0.07	-0.35	-0.02
Pound	AR*100	6.31*	6.59*	2.23	1.91	4.57	6.06*	4.05	4.81	-1.84	0.79	3.55
	Sharpe ratio	0.61	0.61	0.23	0.21	0.42	0.64	0.38	0.47	-0.17	0.07	0.35
Mark	AR*100	9.33**	9.09**	1.88	9.82***	11.40***	9.28**	7.18*	7.18*	-3.75	5.59	6.70
	Sharpe ratio	0.89	0.84	0.19	1.21	1.05	0.90	0.69	0.69	-0.35	0.54	0.67
T-bills	AR*100	3.24**	4.17**	0.83	4.65***	1.92	-0.16	0.38	1.62	1.62	2.63*	2.09
	Sharpe ratio	0.84	0.97	0.20	1.51	0.45	-0.04	0.09	0.40	0.38	0.62	0.54
Average	AR*100	1.51	5.61	-1.28	7.53	2.31	3.25	1.70	-1.18	-2.64	-1.63	1.52
	Sharpe ratio	0.28	0.42	0.03	0.63	0.27	0.28	0.17	0.10	-0.13	0.00	0.21

[a] Sample periods of financials (pound, mark, and T-bills) are from 1980 through 1984.

[b] MAB: Simple Moving Average with % Price Band DMC: Dual Moving Average Crossover CHL: Outside Price Channel LSO: L-S-O Price Channel MII: M-II Price Channel
DRI: Directional Indicator RNQ: Range Quotient REF: Reference Deviation DRM: Directional Movement ALX: Alexander's Filter Rule

[c] AR*100 indicates the annual mean net return.

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. t-tests are used to measure the statistical significance of trading returns.

Table 6. Annual Mean Net Returns for Ten Trading Systems, 1985-2002.[a]

Contract		Trading System[b]										
		MAB	DMC	CHL	LSO	MII	DRI	RNQ	REF	DRM	ALX	Average
Corn	AR*100[c]	-2.65	-5.55	-2.69	-6.58	-14.36	-3.29	-9.13	0.94	-25.14	-7.51	-7.60
	Sharpe ratio	-0.17	-0.28	-0.15	-0.37	-0.72	-0.23	-0.49	0.05	-1.34	-0.45	-0.41
Live Cattle	AR*100	-3.52	-6.07	-3.75	-0.75	-9.08	-1.81	-8.99	-3.80	-4.94	-0.48	-4.32
	Sharpe ratio	-0.42	-0.45	-0.33	-0.06	-0.67	-0.23	-0.74	-0.32	-0.38	-0.05	-0.36
Pork Bellies	AR*100	-13.93	-3.96	-3.03	-0.24	-0.67	-2.64	-9.72	2.62	-14.49	-1.73	-4.78
	Sharpe ratio	-0.57	-0.11	-0.10	-0.01	-0.02	-0.11	-0.29	0.08	-0.45	-0.06	-0.16
Lumber	AR*100	-5.40	-8.85	-5.47	13.46***	-0.50	-0.50	1.66	0.45	-4.70	-8.04	-1.79
	Sharpe ratio	-0.27	-0.35	-0.23	0.58	-0.02	-0.02	0.07	0.02	-0.20	-0.36	-0.08
Soybeans	AR*100	-11.04	-3.65	-5.14	-4.53	-9.68	-6.75	-10.36	-5.36	-15.79	-10.57	-8.29
	Sharpe ratio	-0.89	-0.19	-0.35	-0.29	-0.49	-0.48	-0.58	-0.30	-0.85	-0.67	-0.51
Pound	AR*100	0.24	-0.79	-0.75	0.50	-2.23	0.28	-4.02	-0.95	0.41	0.21	-0.71
	Sharpe ratio	0.03	-0.07	-0.08	0.07	-0.21	0.03	-0.39	-0.09	0.04	0.02	-0.07
Mark	AR*100	-2.34	-0.15	2.54	2.50	-0.17	0.51	-0.62	3.31	-5.21	2.13	0.25
	Sharpe ratio	-0.25	-0.01	0.25	0.30	-0.01	0.05	-0.06	0.29	-0.45	0.20	0.03
T-bills	AR*100	0.13	0.14	-0.03	1.38***	-0.21	0.14	0.08	0.14	0.24	0.63**	0.26
	Sharpe ratio	0.15	0.11	-0.03	1.62	-0.17	0.13	0.06	0.12	0.20	0.53	0.27
Average	AR*100	-4.81	-3.61	-2.29	0.72	-4.61	-1.76	-5.14	-0.33	-8.70	-3.17	-3.37
	Sharpe ratio	-0.30	-0.17	-0.13	0.23	-0.29	-0.11	-0.30	-0.02	-0.43	-0.11	-0.16

[a] Sample periods of financials vary: 1985-2002 for the pound, 1985-1998 for the mark, and 1985-1996 for T-bills.

[b] MAB: Simple Moving Average with % Price Band DMC: Dual Moving Average Crossover CHL: Outside Price Channel LSO: L-S-O Price Channel MII: M-II Price Channel
DRI: Directional Indicator RNQ: Range Quotient REF: Reference Deviation DRM: Directional Movement ALX: Alexander's Filter Rule

[c] AR*100 indicates the annual mean net return.

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. t-tests are used to measure the statistical significance of trading returns.

Table 7. Annual Mean Net Returns for Ten Trading Systems, 1978-2002.[a]

Contract		Trading System[b]										
		MAB	DMC	CHL	LSO	MII	DRI	RNQ	REF	DRM	ALX	Average
Corn	AR*100[c]	-0.99	-2.67	-1.08	-2.42	-8.05	0.11	-4.78	1.81	-19.47	-5.36	-4.29
	Sharpe ratio	-0.06	-0.14	-0.06	-0.14	-0.42	0.01	-0.27	0.10	-1.08	-0.33	-0.24
Live Cattle	AR*100	-3.93	-7.20	-3.35	0.66	-8.91	-1.69	-8.76	-5.28	-6.39	-2.05	-4.69
	Sharpe ratio	-0.36	-0.48	-0.25	0.05	-0.59	-0.18	-0.62	-0.39	-0.44	-0.18	-0.34
Pork Bellies	AR*100	-13.77	-2.27	-7.04	0.40	-4.59	-1.99	-8.98	-4.52	-12.67	-0.16	-5.56
	Sharpe ratio	-0.53	-0.06	-0.23	0.01	-0.13	-0.08	-0.27	-0.14	-0.39	-0.01	-0.18
Lumber	AR*100	-2.08	0.18	-2.39	16.44***	3.86	0.73	5.25	1.94	-2.17	-9.49	1.23
	Sharpe ratio	-0.10	0.01	-0.10	0.71	0.15	0.04	0.21	0.08	-0.09	-0.44	0.05
Soybeans	AR*100	-7.45	-1.25	-4.85	-1.82	-6.84	-5.00	-8.48	-4.12	-10.94	-9.51	-6.03
	Sharpe ratio	-0.50	-0.06	-0.29	-0.10	-0.33	-0.32	-0.44	-0.21	-0.56	-0.57	-0.34
Pound	AR*100	1.56	0.81	-0.10	0.81	-0.75	1.54	-2.26	0.30	-0.08	0.33	0.22
	Sharpe ratio	0.17	0.07	-0.01	0.10	-0.07	0.18	-0.22	0.03	-0.01	0.03	0.03
Mark	AR*100	0.73	2.28	2.36	4.43***	2.87	2.82	2.08	4.33**	-4.82	3.04	2.01
	Sharpe ratio	0.07	0.20	0.23	0.54	0.25	0.29	0.19	0.39	-0.43	0.29	0.20
T-bills	AR*100	1.04**	1.32**	0.22	2.34***	0.42	0.05	0.17	0.58	0.65	1.21**	0.80
	Sharpe ratio	0.47	0.52	0.09	1.29	0.16	0.02	0.07	0.24	0.26	0.48	0.36
Average	AR*100	-3.11	-1.10	-2.03	2.61	-2.75	-0.43	-3.22	-0.62	-6.99	-2.75	-2.04
	Sharpe ratio	-0.11	0.01	-0.08	0.31	-0.12	-0.01	-0.17	0.01	-0.34	-0.09	-0.06

[a] The sample periods of financials vary: 1980-2002 for the pound, 1980-1998 for the mark, and 1980-1996 for T-bills.

[b] MAB: Simple Moving Average with % Price Band DMC: Dual Moving Average Crossover CHL: Outside Price Channel LSO: L-S-O Price Channel MII: M-II Price Channel
DRI: Directional Indicator RNQ: Range Quotient REF: Reference Deviation DRM: Directional Movement ALX: Alexander's Filter Rule

[c] AR*100 indicates the annual mean net return.

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. t-tests are used to measure the statistical significance of trading returns.

Figure 1. Annual Mean Net Returns for Corn, 1978-2002.

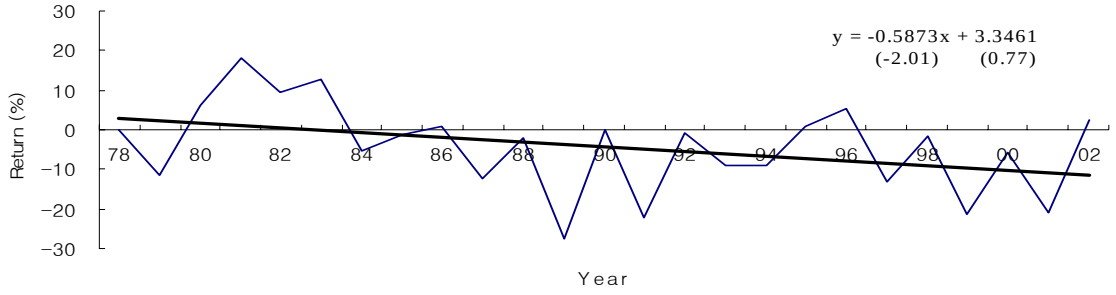

Figure 2. Annual Mean Net Returns for Live Cattle, 1978-2002.

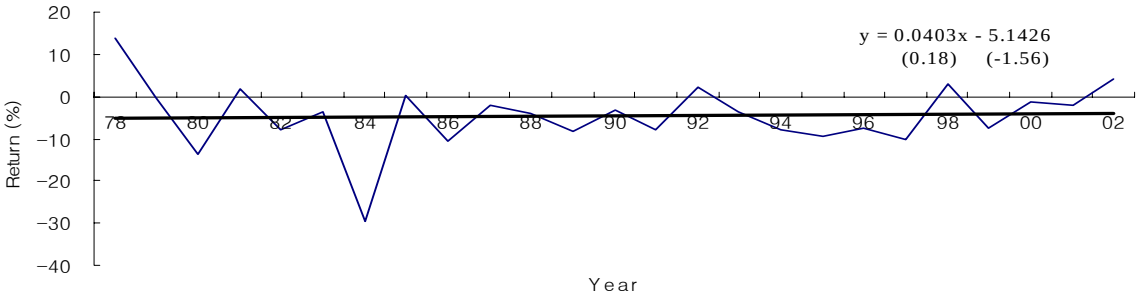

Figure 3. Annual Mean Net Returns for Pork Bellies, 1978-2002.

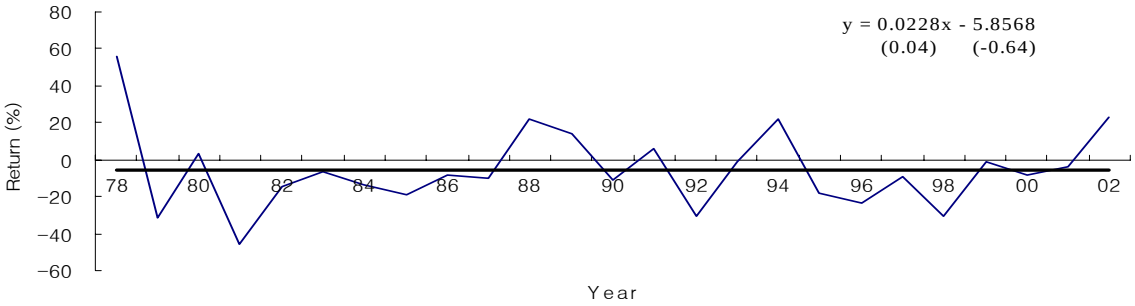

Figure 4. Annual Mean Net Returns for Lumber, 1978-2002.

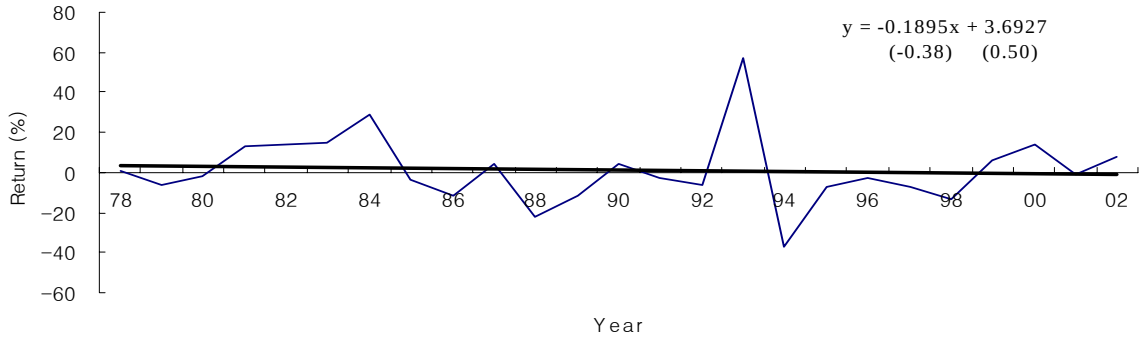

Figure 5. Annual Mean Net Returns for Soybeans, 1978-2002.

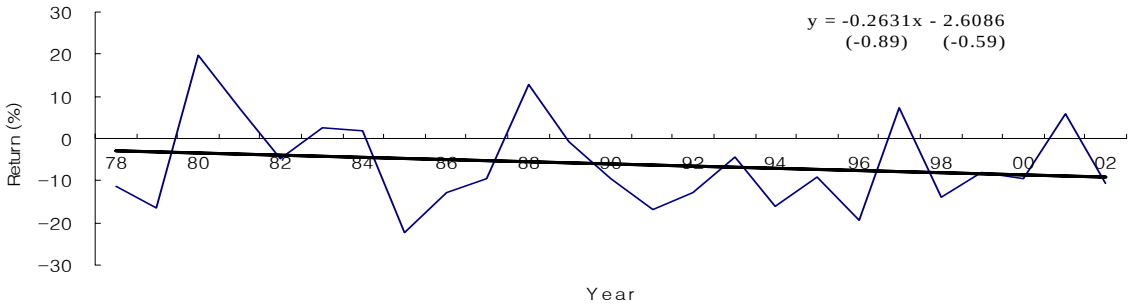

Figure 6. Annual Mean Net Returns for British Pound, 1980-2002.

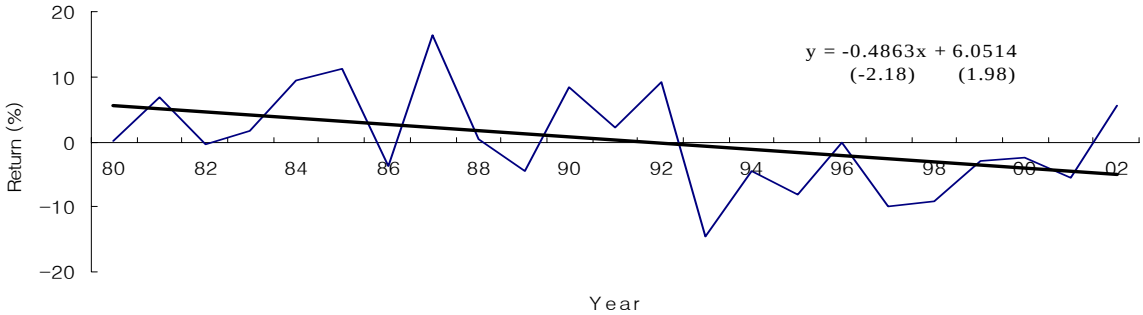

Figure 7. Annual Mean Net Returns for Deutsche Mark, 1980-1998.

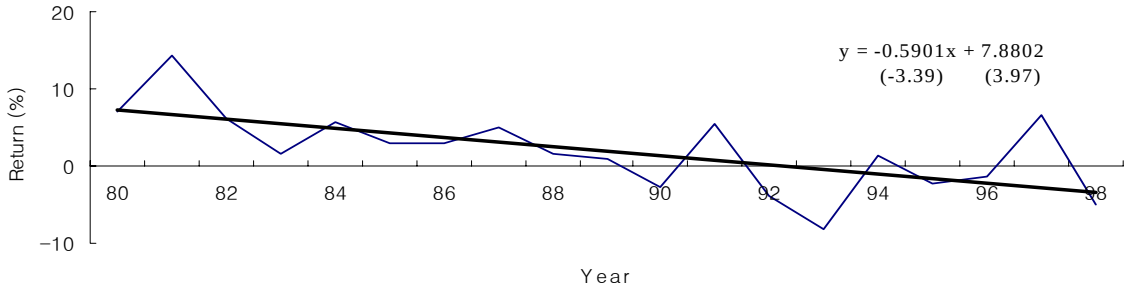

Figure 8. Annual Mean Net Returns for Treasury Bills, 1980-1996.

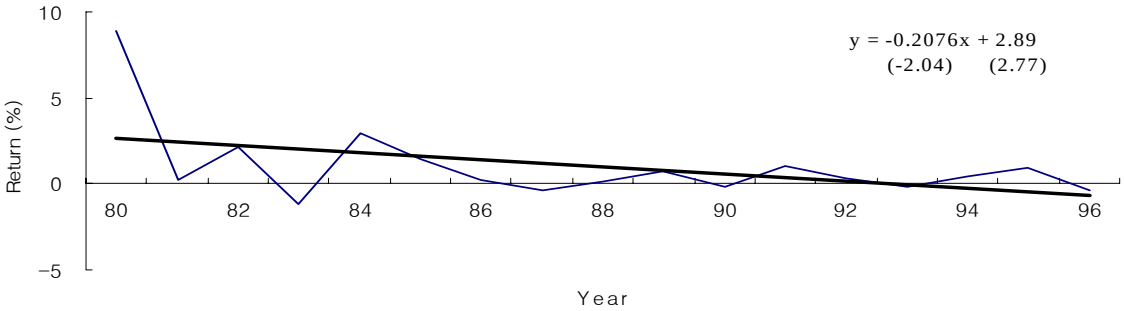

Figure 9. Annual Mean Net Returns for the MAB System

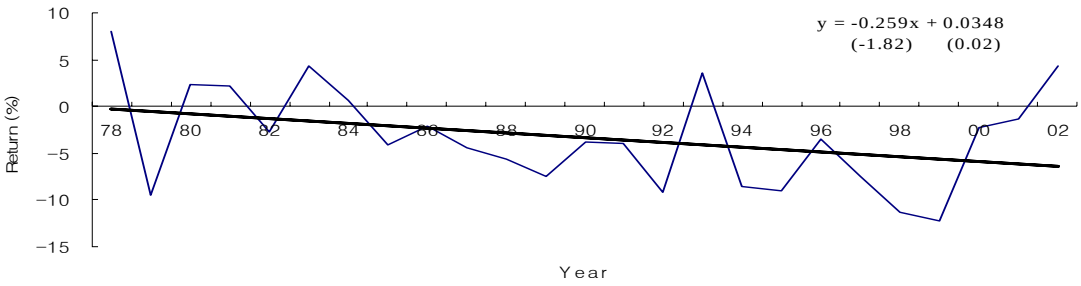

Figure 10. Annual Mean Net Returns for the DMC System

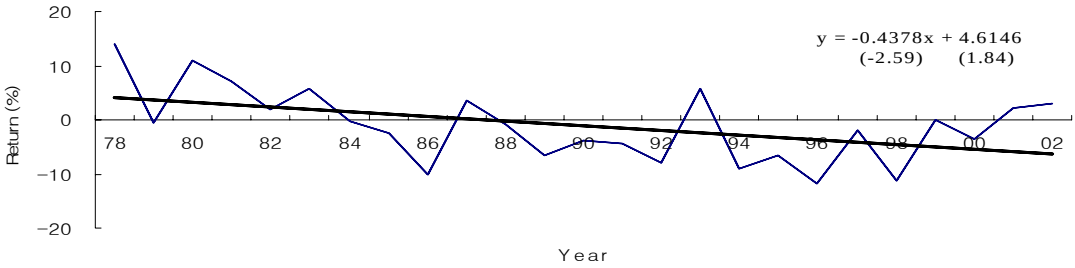

Figure 11. Annual Mean Net Returns for the CHL System

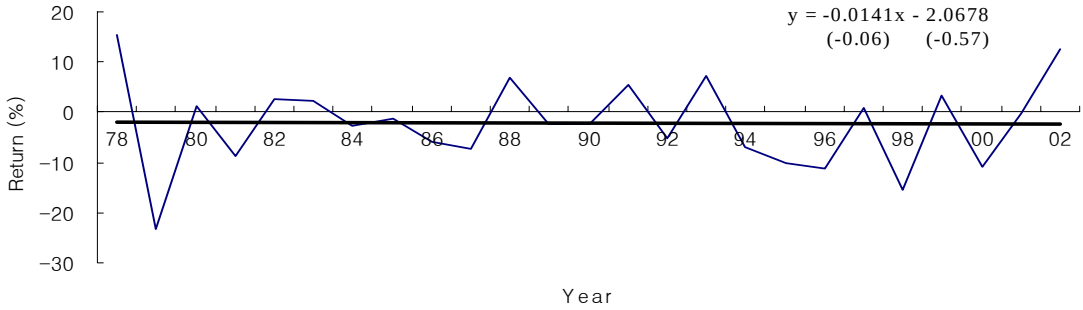

Figure 12. Annual Mean Net Returns for the LSO System

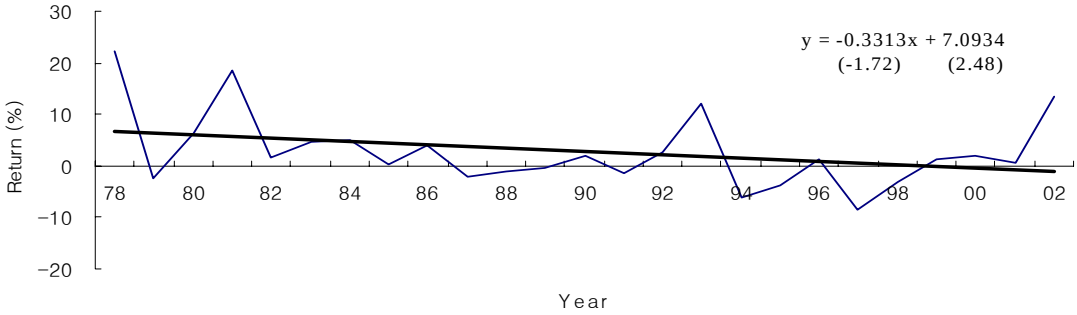

Figure 13. Annual Mean Net Returns for the MII System

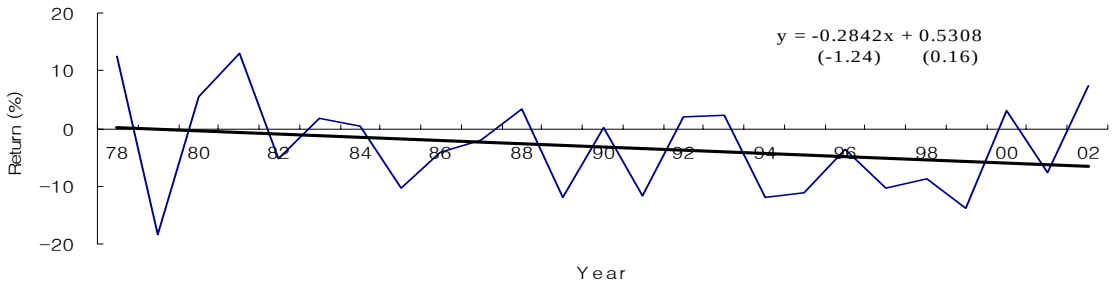

Figure 14. Annual Mean Net Returns for the DRI System

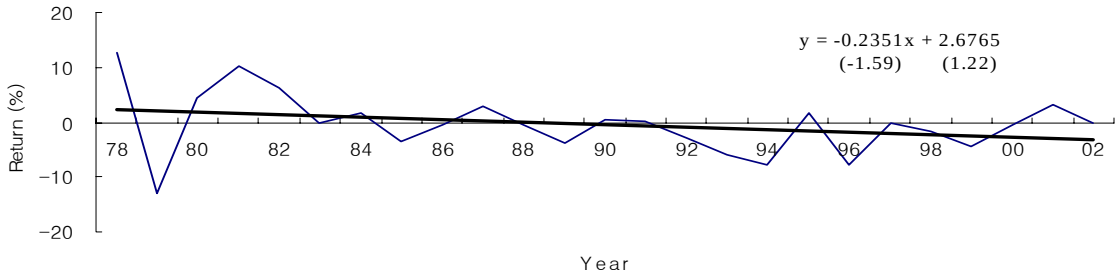

Figure 15. Annual Mean Net Returns for the RNQ System

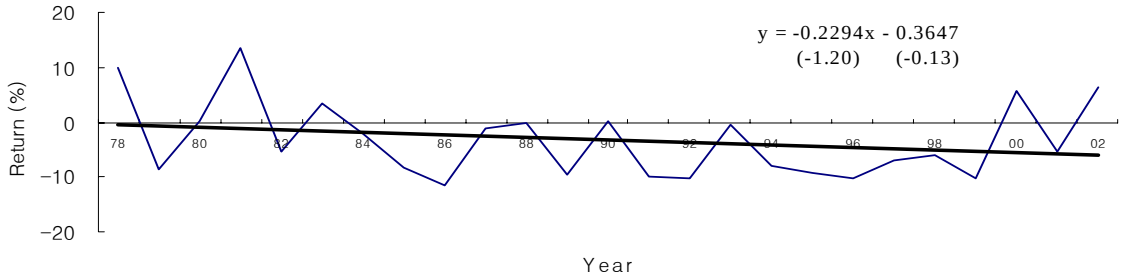

Figure 16. Annual Mean Net Returns for the REF System

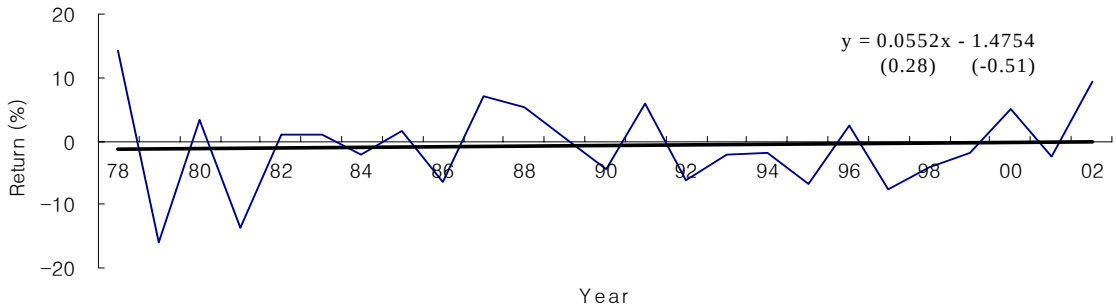

Figure 17. Annual Mean Net Returns for the DRM System

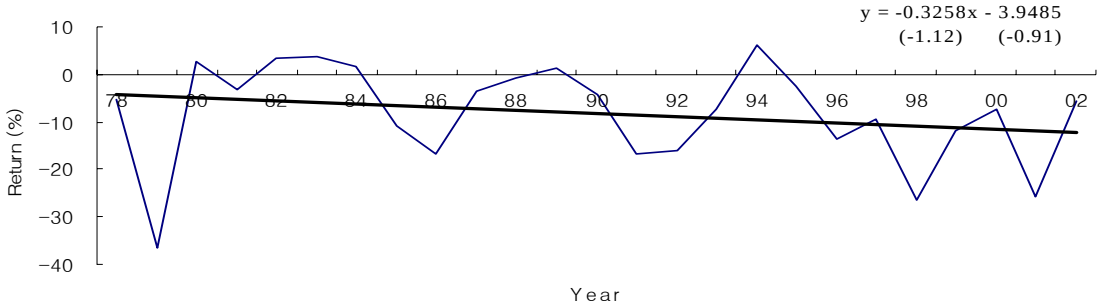

Figure 18. Annual Mean Net Returns for the ALX System

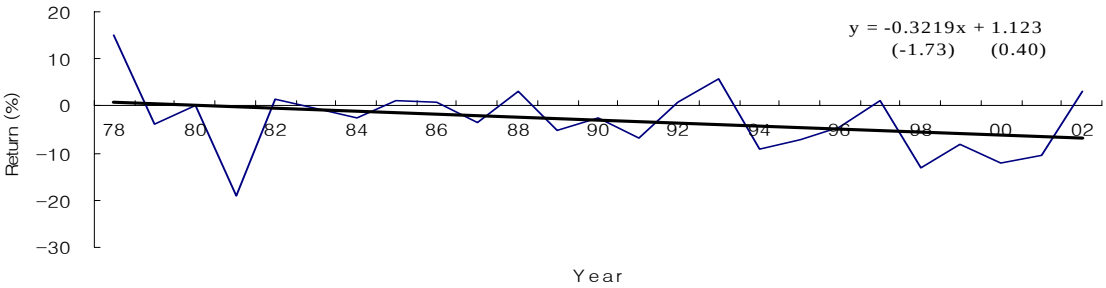

Figure 19. Aggregate Portfolio Annual Mean Net Returns across Trading Systems and Markets, 1978-2002.