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

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Abstract

Numerous empirical studies investigate the profitability of technical trading rules in a wide variety of markets and many find 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 study mitigates data snooping problems by confirming the results of a previous study and then replicating the original testing procedure on a new body of data. Results indicate that technical trading profits have gradually declined over time in 12 futures markets. Substantial technical trading profits during the 1978-1984 period are no longer available in the 1985-2003 period.

Key words: technical analysis, trading systems, data-snooping, commodities, forecasting

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Technical analysis is a method of forecasting price movements based on patterns in past prices.[1] Technical methods include chart analysis, cycle analysis, and computerized technical trading systems. Academic research on technical analysis generally focuses on technical trading systems, which can be readily expressed in mathematical form. Technical trading systems are designed to automatically recognize predictable trends in commodity prices under the expectation that the trends will continue in the future. A system consists of a set of trading rules that result from different possible parameterizations of the system and each rule generates trading signals (long, short, or out of the market) based on a particular set of parameter values. Popular technical trading systems include moving averages, channels, and momentum oscillators (e.g., Schwager 1996).

There is considerable evidence that both speculators and hedgers in futures markets attribute a significant role to technical analysis. Surveys show that many commodity trading advisors (CTAs) and hedge fund managers rely heavily on computer-guided technical trading systems (Billingsley and Chance 1996; Fung and Hsieh 1997). These traders can represent a relatively large proportion of total trading volume in many futures markets (e.g., Irwin and Holt 2004). Within the agricultural sector, market advisory services, which provide specific hedging advice to farmers about marketing crops and livestock, also make substantial use of technical systems. For example, a prominent service recently began offering a “systematic hedger program” where hedge signals are generated automatically based on 9- and 18-day moving averages (Doane’s Agricultural Report, 2004).

In contrast to many market participants, academics tend to be skeptical about technical analysis based on the belief that markets are efficient, at least with respect to historical prices. In efficient markets (Fama 1970), any attempt to make economic profits by exploiting currently available information, such as past prices, is futile. It should be noted that views on technical analysis are not universally negative within the field of agricultural economics. Brorsen and Anderson (1999) report that about 10% of Extension marketing economists use technical analysis to forecast prices.

Given the importance of the topic to understanding market price behavior, numerous empirical studies investigate the profitability of technical trading rules and many find evidence of positive technical trading profits (e.g., Lukac, Brorsen, and Irwin 1988; Brock, Lakonishok, and LeBaron 1992; Chang and Osler 1999). For example, Lukac, Brorsen, and Irwin (1988) find that four technical trading systems, including the dual moving average crossover and the price channel, yield statistically significant monthly portfolio net returns of 1.89% to 2.78% during 1978-1984 that do not appear to be compensation for bearing systematic risk.[2] Such findings potentially represent a serious challenge to the efficient markets hypothesis and our understanding of price behavior in speculative markets. However, there is reason for skepticism about technical trading profits reported in previous studies. Cochrane (2001, p. 25) argues, "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." As the term "dredging the data" colorfully highlights, data snooping concerns drive much of the skepticism.

Data snooping occurs when a given set of data is used more than once for purposes of inference or model selection (White 2000). If such data snooping occurs, any successful results may be spurious because they could be obtained by chance with exaggerated significance levels (e.g., Denton 1985; Lo and MacKinlay 1990). 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 (2006). 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. Even if a researcher considers only a single alternative for a choice variable (e.g., an in-sample period) in an ad-hoc fashion, it is likely to be strongly affected by similar previous research. Moreover, when there are many researchers analyzing the same dataset they collectively snoop the data. Collective data snooping is potentially even more dangerous because it is not easily recognized by each individual researcher (Denton 1985).

As a method to deal with data snooping problems, a number of studies in the economics literature suggest replicating previous results on a new body of data (e.g., Lovell 1983; Schwert 2003; Sullivan, Timmermann, and White, 2003). Tomek (1993) provides important guidelines with regard to replication. As a solution to the problem of unstable empirical results due to data snooping and other specification problems, he advocates a "confirmation" and "replication" methodology, where confirmation (or "duplication") is an attempt to fit the original model with the original data and replication is an effort to fit the original specification to new data. For a study in the technical trading literature to be a good candidate for confirmation and 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 ‘written in stone’ at the point in time the study was published. Third, the original work should be old enough that a follow-up study can have a sufficient sample size.

Only a handful of empirical studies on technical trading replicate previously published results (e.g., Sullivan, Timmermann, and White 1999; Olson 2004) and the focus in these studies has been on financial and currency markets. Therefore, to determine whether technical trading rules have been profitable in US futures markets this article confirms and replicates a well-known 1988 study by Lukac, Brorsen, and Irwin. In the technical trading literature, Lukac, Brorsen, and Irwin’s study meets the above three conditions. This study included comprehensive tests on 12 U.S. futures markets using a wide range of technical trading systems, trading rule optimization, and out-of-sample verification. An additional benefit in the present context is that the 12 futures markets are weighted towards agricultural and natural resource commodities (commodities: corn, soybeans, cattle, pork bellies, sugar, cocoa and lumber; metals: copper and silver; financials: British pound, Deutsche mark and U.S. treasury-bills). The original framework is duplicated as closely as possible by preserving all the trading model assumptions in Lukac, Brorsen, and Irwin’s work, such as trading systems, markets, optimization method, out-of-sample verification length, transaction costs, rollover dates, and other important assumptions.

In the confirmation step, the annual portfolio mean gross returns obtained by Lukac, Brorsen, and Irwin (1988) over 1978-1984 are compared to gross returns calculated by applying our trading model to the original optimal parameters. Gross returns are a better performance measure to compare results from both studies because they are not contaminated by differences in the way transactions costs can be handled. In addition, correlation coefficients between annual net returns derived from our trading model and the original results are calculated and sign consistency of annual net returns from both trading models is checked. In the replication step, the trading model is applied to a new set of data from 1985-2003. Parameters of each trading system are optimized based on the mean net return criterion and out-of-sample performance is evaluated. Statistical significance of technical trading returns is measured via a stationary bootstrap, which is generally applicable to weakly dependent stationary time series. By minimizing, if not eliminating, the deleterious impacts of data snooping this study provides a true out-of-sample test for the profitability of technical trading rules in U.S. futures markets.

Data

Lukac, Brorsen, and Irwin (1988) investigated 12 futures markets over the 1975-1984 period. Their out-of-sample period begins in 1978 since data for three years from 1975-1977 are used to optimize the first set of trading rules. The current study extends the sample period to the 1975-2003 for the same 12 futures markets, which include highly traded agricultural commodities, metals, and financials. Specifically, corn and soybeans from the Chicago Board of Trade (CBOT), live cattle, pork bellies, lumber, British pound, Deutsche mark, and U.S. treasury-bills from the Chicago Mercantile Exchange (CME), silver and copper from the Commodity Exchange, Inc. (COMEX), and sugar (world) and cocoa from the Coffee, Sugar, and Cocoa Exchange (CSCE). Daily price data for each futures market from 1975 through 2003 are used to evaluate in- and out-of-sample performance of the technical trading rules, with the exception of the three financials that have slightly shorter sample periods: 1977-2003 for the British pound, 1977-1998 for the Deutsche mark, and 1977-1996 for treasury-bills. The full out-of-sample period, 1978-2003, is divided into two sub-periods: 1978-1984 and 1985-2003, for the purposes of confirmation and replication. The first sub-period is the same as that analyzed in the original 1988 study by Lukac, Brorsen, and Irwin.

It is important to incorporate accurate daily price limits into the trading model because price movements for certain futures contracts are occasionally locked at the daily allowable limits. Since trend-following trading rules typically generate buy (sell) signals in up (down) trends, the daily price limits imply that buy (sell) trades actually will be 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 limit 'locked' price levels. The history of daily price limits for each contract is obtained from exchange statistical yearbooks and the annual *Reference Guide to Futures/Options Markets* and *Source Book* issues of *Futures* magazine.

Trading Model

The trading model is a general procedure to process input data and produce the required output by programming trading strategies and other relevant assumptions. It typically consists of input data, technical trading systems, performance measures, the optimization method, and other assumptions. As noted previously, we duplicate Lukac, Brorsen, and Irwin's (1988) trading model as closely as possible for the purpose of confirmation and replication, thereby employing the same trading systems, optimization method, out-of-sample verification length, transaction costs, rollover dates, and other assumptions. Each component of the trading model is described next.

Input Data

The trading model uses daily futures price series as the input data. Although there are various ways to construct a series of futures data to simulate technical trading systems, we employ dominant contracts, the ones with the highest open interest, because they reflect the most important market characteristics (Dale and Workman 1981). In this approach, an existing position in the current ‘dominant’ contract is liquidated on a rollover date and a new position in the next ‘dominant’ contract is simultaneously established according to a trading signal generated by applying a given trading rule to past data of the new ‘dominant’ contract (Lukac, Brorsen, and Irwin 1988; Lukac and Brorsen 1990; Silber 1994). We assume that the current dominant contract rolls over the new dominant contract on the second Tuesday of the month preceding its delivery month. According to Lukac, Brorsen, and Irwin (1988), this approach is consistent with the price series used by actual technical traders.

Technical Trading Systems

A technical trading system is composed of a set of trading rules that can be used to generate trading signals. Most trading systems have one or two parameters that are used to vary the timing of trading signals. 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. In this study, the 12 technical trading systems examined by Lukac, Brorsen, and Irwin (1988) are duplicated. The 12 trend-following technical trading systems consist of moving averages, price channels, momentum oscillators, filters, and a combination system. Table 1 provides general information about the 12 trading systems. According to Lukac, Brorsen, and Irwin (1988), 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. Details on the trading mechanics and parameters for each of the12 trading systems can be found in Lukac, Brorsen, and Irwin (1990).

Performance Measures

Past research that evaluates the performance of technical trading systems in futures markets, including Lukac, Brorsen, and Irwin's study, often measured trading profits in terms of dollar returns and/or percent returns to total investment. However, several more recent studies (e.g., Kho 1996; Szakmary and Mathur 1997; Sullivan, Timmermann, and White 1999) on futures markets measure a holding period return or the continuously compounded (log) return per unit. Although defining a rate of return may be problematical because there is no initial investment except for a margin deposit in the futures market, Kho (1996, p. 252) argues 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." The continuously compounded daily gross return on a technical trading rule *k* at time *t* can be calculated by:

$$(1) \qquad r^{g}_{k,t+1} = [\ln(P_{t+1}) - \ln(P_t)]S_{k,t},$$

where P_{t+1} and P_t are futures prices at time $t+1$ and *t*, respectively, and $S_{k,t}$ 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.[3] Measuring trading returns on a daily basis is consistent with the process of the daily settlement (marking-to-market) in the futures market.

The net return provides a measure of trading returns beyond transaction costs. Thus, net returns are used as a performance measure to choose optimal trading rules during in-sample periods and evaluate out-of-sample performance. Net return per trade is calculated by subtracting estimated transaction costs per trade from the gross return per trade. This calculation includes every rollover trade. Hence, the daily net trading return is given by:

$$(2) \qquad r_{k,t+1} = r^{g}_{k,t+1} + d_{t+1}\left(\frac{n_k}{N^{in}_k}\right)\ln(1-c),$$

where n is the number of round-trip trades for a contract, N^{in} is the number of days "in" the market (e.g., $N^{in} = N - N^{out}$, where N^{out} is the number of days "out" of the market), d_{t+1} is an indicator variable having a value of 1 for in-days and 0 for out-days, and c is round-trip proportional transaction costs.

Jensen's (1978) definition of an efficient market implies that a technical trading rule is profitable only if its risk-adjusted profits exceed transaction costs incurred from implementing trades. Several techniques have been used in the technical trading literature to explicitly measure the risk-adjusted performance of trading rules. One of the most widely used risk-adjusted performance criteria is the Sharpe ratio, which accounts for the excess return per unit of total risk. Since futures traders can deposit treasury-bills for margin requirements, there is no need to sacrifice the risk-free return in order to participate in an alternative investment. Thus, the ex post Sharpe ratio (SR_k) for trading rule *k* can be calculated by:

(3) $$SR_k = \bar{r}_k / \hat{\sigma}_k,$$

where $\bar{r}_k$ and $\hat{\sigma}_k$ indicate the annualized mean net return and standard deviation, respectively, during a sample period.

Transactions Costs

It is apparent that transaction costs are an important factor that influences net trading returns. Following Lukac, Brorsen, and Irwin, we apply round-trip proportional transaction costs of $100 per contract per round-trip trade for the entire sample period. The $100 transaction cost includes both the brokerage commission and the bid-ask spread, which is also referred to as execution costs, liquidity costs, or skid error.[4] Since data for the bid-ask spread in futures markets are not typically available, execution costs normally must be estimated. Bid-ask spread estimates for the

12 futures markets analyzed in this article range from $3-$25 per contract (e.g., Ma, Peterson, and Sears, 1992; Ferguson and Mann, 2001).[5] These estimates imply that the brokerage commission assumed in Lukac, Brorsen, and Irwin's study would be equal to or greater than $75 per round-turn trade, which is quite conservative compared to those of other studies (e.g., Szakmary and Mathur 1997; Wang 2000). Commissions through discount brokers are around $12.50 per round turn (Lukac, Brorsen, and Irwin 1988; Lukac and Brorsen 1990), and even lower for both high volume traders and electronic trades introduced in the early 1990s. Thus, a second scenario for transaction costs is assumed that lowers brokerage commissions after 1984 as follows: $50 for 1985-1994 and $25 for 1995-2003. As a result, total transaction costs for the second scenario are assumed to be $100 for 1978-1984, $75 for 1985-1994, and $50 for 1995-2003.

The dollar transaction costs are converted into a percentage transaction cost per unit by dividing the dollar transaction costs by an average contract value, which is in turn obtained from multiplying the number of units of a contract by an average closing price. Since the average contract value differs across contracts, the percentage transaction cost also differs. Given the dollar transaction costs, the larger the contract value, the less the percentage transaction costs.

Optimization and Other Assumptions

According to survey results by Brorsen and Irwin (1987), most CTAs select the parameters of trading systems by optimizing over historical data, although there is no consensus on how much data to use to select the parameters.[6] Thus, the same three-year re-optimization method as in Lukac, Brorsen, and Irwin (1988) is applied 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 with 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 technical trading systems are adaptive and all trading results are out-of-sample.

For futures markets having daily price limits, no trading occurs when a price moves the daily allowable limit above or below the previous day's settlement price. Thus, neither the current position is closed out nor a new position is taken if the high, low, and closing prices in a day are equal (lock-limit day), or if the execution price (e.g., today’s closing or next day’s opening prices) is up or down the daily allowable limit. Instead, the order is deferred and placed at the next execution price as long as the new trading signal still holds and the price is not subject to the daily price limit. Several other important assumptions are included in the trading model. First, all trading is on a one contract basis, i.e., only one contract is used for each transaction. Second, no pyramiding of positions or reinvestments of profits is allowed. Third, sufficient funds are assumed available to meet the margin requirement that may occur due to trading losses.

Statistical Tests

Most previous technical trading studies apply the traditional *t*-test, standard bootstrap, or model-based (parametric) bootstrap to measure statistical significance of technical trading profits.

However, the *t*-test and standard bootstrap methods, which assume independently and identically distributed (IID) observations, may not be relevant for high-frequency time series data that is highly likely to be time-dependent. The model-based bootstrap can also deliver inconsistent estimates if the structure of serial correlation is not tractable or mis-specified (Maddala and Li, 1996, p. 465). A stationary bootstrap can preserve the dependence and stationarity of the original time series in a re-sampled pseudo-time series by resampling blocks of random length from the original series, where the block length follows a geometric distribution (Politis and Romano 1994). Thus, the stationary bootstrap can provide improved statistical tests compared to other statistical methods.

The performance statistic for testing whether technical trading rule *k* generates superior mean net returns is defined as the difference in mean net returns between the trading rule and a zero return benchmark (e.g., Peterson and Leuthold 1982; Lukac, Brorsen, and Irwin 1988; Lukac and Brorsen 1990). It is constructed as:

$$(4) \qquad \overline{Y}_k = N^{-1}\sum_{t=0}^{N-1} Y_{k,t+1},$$

where $Y_{k,t+1} = r^G_{k,t+1} + d_{t+1}(n_k / N^{in}_k)\ln(1-c),$ since zero mean profits are assumed as a benchmark. The null and alternative hypotheses are then defined as $H_0 : E(Y) = 0$ and $H_1 : E(Y) > 0.$ Bootstrap samples are generated using the following resampling algorithm for the stationary bootstrap proposed by White (2000, p. 1104): (i) start by selecting a smoothing parameter $q = 1/b = q_N,\ 0 < q_N \le 1,\ q_N \to 0,\ Nq_N \to \infty$ as $N \to \infty$; since *q* is inversely related to the block length, a larger value of *q* may be used for data with little dependence, while a smaller value of *q* may be appropriate for data with more dependence; (ii) set $t = 0$ and draw $\eta(0)$ at random, independently and uniformly from $\{0, \ldots, N-1\},$ where $\eta(t)$ denotes a random index at time *t*; (iii) increment *t* and if $t > N-1,$ stop, otherwise, draw a standard uniform random variable *U* (supported on [0,1]) independent of all other random variables: (a) if $U < q,$ draw $\eta(t)$ at random, independently and uniformly from $\{0,\ldots,N-1\};$ (b) if $U \geq q,$ set $\eta(t) = \eta(t-1)+1$, or if $\eta(t) > N-1,$ reset $\eta(t) = 0;$ and (iv) repeat (iii). By implementing this resampling algorithm with a smoothing parameter $q = 0.1,$ 1,000 bootstrap samples of $\overline{Y}_{k,i}^{*} = N^{-1}\sum_{t=0}^{N-1} Y_{k,\eta(t)+1}^{*},$ (i = 1, …, 1,000), are generated. The bootstrap *p*-value is obtained by comparing the sample value of $\overline{Y}_k$ to the quantiles of $\overline{Y}_{k,i}^{*}$.

Confirmation Results

To confirm Lukac, Brorsen, and Irwin's original out-of-sample results for 1978-1984, their annual portfolio mean gross returns are compared to gross returns calculated by applying the trading model of this study to the original optimal parameters. Gross returns are a better performance measure to compare results from both studies because they are not contaminated by differences in the way transactions costs can be handled. Since Lukac, Brorsen, and Irwin calculated returns by 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, continuously compounded returns calculated in this study are converted into the same return measure. The formula used is as follows:

(5) $$r_{LBI} = (r_{PI} \times \overline{V})/\{[(M/100)\times\overline{V}]/0.3\},$$

where r_{LBI} denotes returns measured by the total investment method, r_{PI} denotes continuously compounded returns, $\overline{V}$ denotes average contract value, and *M* denotes percent margin.[7] The formula can be reduced to:

(6) $r_{LBI} = r_{PI} \times (30 / M)$.

In the original study, the percent margin was assumed to be 0.5% for treasury-bills, 5% for currencies, and 10% for other contracts. Therefore, Lukac, Brorsen, and Irwin's returns can be approximated by multiplying continuously compounded returns by 60 for treasury-bills, 6 for currencies, and 3 for other contracts.

Table 2 provides the confirmation results. The first three columns, labeled (1) to (3) in the table, present Lukac, Brorsen, and Irwin's original out-of-sample results and include annual portfolio gross returns, net returns, and transaction costs for each trading system across the 12 futures markets.[8] The next three columns, labeled (4) to (6), show the corresponding results obtained from applying our trading model to the original optimal parameters, and the last three columns, labeled (7) to (9), indicate results obtained from applying our trading model to our optimal parameters. When comparing the original results (column (1)) and our results with the original optimal parameters (column (4)), the trading model developed in this paper generates similar annual gross returns to those of the original study for the DMC, DRM, PAR, and DRP systems. For other trading systems, however, gross returns are quite different. In particular, the 5 trading systems (MAB, LSO, DRI, RNQ, and REF) that generated negative gross returns in the original study produce positive gross returns using our trading model. Both studies generate positive gross returns in the CHL, MII, and ALX systems, but differences in the size of gross returns are non-trivial. The last set of results (column (7)) show that for 9 of the 12 trading systems annual gross returns for our trading model using our optimal parameters are higher than or equal to those for our trading model using the original optimal parameters, although average gross returns are quite similar (42.2% and 35.8%, respectively). Average gross returns for our trading model using our optimal parameters also are not dramatically different from the returns for the original model using the original optimal parameters (42.2% and 28.2%, respectively). However there are large differences in transaction costs.

Similar results are found in the correlation analysis. Since Lukac, Brorsen, and Irwin reported only annual net returns for each trading system across markets and sample years, we calculate correlation coefficients between annual net returns derived from our trading model and theirs. For each trading system, 78 pairs of annual net returns are obtained.[9] Results show that correlation coefficients range from 0.60 for the CHL system to 0.82 for the MII system, with an average correlation coefficient of 0.71. The CHL, DRI, RNQ, ALX, and PAR systems have lower correlation coefficients than the average. In addition, for 650 of 858 possible cases (about 76%) annual net returns from both trading models have the same signs.[10] Sign consistency is lower than average in the MAB, CHL, DRI, RNQ, and REF systems, ranging 67% to 72%.

Differences in results versus the original study can be traced to several factors. Lukac, Brorsen, and Irwin (1988) used a different version of the CHL system from that in Barker (1981), while this study adopted Barker's original version because of its simplicity and generality. Results for the ALX, PAR, and DRP may differ because the initial trend and extreme points (local high and low prices) can be determined arbitrarily by researchers. The DRM system may also produce different returns, depending on how an initial entry point into trading is set. On the other hand, the continuously compounded returns used in this study have slight downward (upward) biases against Lukac, Brorsen, and Irwin's positive (negative) returns calculated by the total investment method. In addition, when converting dollar transaction costs into percentage transaction costs, the average contract value may differ depending on which prices are used in the calculation. Other sources, such as programming errors, clerical errors, and differences in data (original prices and daily price limits), may also cause differences in results. For example, several clerical errors were found in table A.12 in Lukac, Brorsen, and Irwin (1990), which includes optimal parameters for the ALX system. As another example, results for the MAB system in the original study are questionable. Since both the MAB and the DMC systems are based on moving averages, they tend to produce similar returns. However, gross returns for the two systems in Lukac, Brorsen, and Irwin's study have the opposite sign and the magnitude of the difference in returns between the two systems appears to be excessively large (83.2% per year in terms of the annual net return). In the light of the positive gross returns for the MAB system generated in both sets of results for the present study, this points towards some type of programming error for the MAB system in the original study.

Despite the differences in results detailed above, average gross returns across the 12 systems for our trading model using our optimal parameters and Lukac, Brorsen, and Irwin's original optimal parameters are quite similar. Moreover, average gross returns for our trading model using our optimal parameters are comparable to those for the original model using the original optimal parameters, although there are large differences in transaction costs. Overall, we find even more evidence of profits than in the original study, confirming the basic thrust of Lukac, Brorsen, and Irwin's conclusions.

Replication Results

The next step in the procedure is to replicate Lukac, Brorsen, and Irwin's (1988) trading model on a new set of data from 1985-2003. Parameters of each trading system are optimized based on the mean net return criterion using the past three years of price data and the optimal parameters are used for the next year's out-of-sample trading. The performance of optimal trading rules for each sample period is reported in tables 3 and 4. The original sample of 1978-1984 is included in order to apply consistent statistical tests to the entire time period under study.[11]

As mentioned above, statistical significance tests on technical trading returns are performed by implementing the stationary bootstrap algorithm. In this re-sampling procedure, a bootstrap sample, represented by a mean net return, is obtained by randomly resampling daily net returns during a sample period. A bootstrap smoothing parameter of 0.1 is used and implies a mean block length of 10. The smoothing parameter produces serial dependence in the net return series and the length of blocks is selected randomly based on a geometric distribution. By repeating the procedure 1,000 times for individual trading systems and an equally weighted portfolio of 12 trading systems, we construct 1,000 bootstrap samples and obtain a *p*-value by comparing the actual mean net return for a sample period to the quantiles of the 1,000 bootstrap samples. A slightly different procedure is used to bootstrap portfolio returns for the 12 markets. Specifically, since trading days differ slightly from market to market, monthly return series on an equally weighted portfolio of 12 markets for each trading system and 1,000 bootstrap samples are constructed with a bootstrap smoothing parameter of one under the assumption that monthly net returns are independent.[12]

As shown in table 3, during the first out-of-sample period (1978-1984 for agricultural commodities and metals; 1980-84 for financials) technical trading strategies generate economically and statistically significant profits in 6 of 12 markets. Specifically, significant annual mean net returns are found in corn by 4 (LSO, MII, DRI, and RNQ) out of the 12 systems, lumber by 5 systems (DMC, LSO, MII, DRI, and RNQ), sugar by 5 systems (MII, RNQ, DRM, ALX, and DRP), silver by 3 systems (ALX, PAR, and DRP), Deutsche mark by 9 systems (MAB, DMC, MII, DRI, RNQ, REF, DRM, PAR, and DRP), and treasury-bills by 6 systems

(MAB, LSO, DRM, ALX, PAR, and DRP). An equally weighted portfolio of the 12 trading systems generates statistically significant annual mean net returns in 4 markets: 24.48% for sugar, 21.65% for silver, 7.64% for mark, and 2.37% for treasury-bills. The corresponding Sharpe ratios are 0.74, 0.80, 0.96, and 0.76, respectively. All of the 12 trading systems, except the CHL system, show significant returns in more than one market. Among the trading systems, 5 systems (MII, DRI, REF, DRM, and DRP) generate significant returns (6.42%, 4.35%, 6.04%, 8.09%, and 5.52%, respectively) for an equally weighted portfolio of 12 markets, with Sharpe ratios ranging from 0.50 to 0.67. Lukac, Brorsen, and Irwin (1988) found that 4 systems (DMC, CHL, MII, and DRP) had statistically significant portfolio mean net returns during the same sample period. The portfolio annual mean net return across the 12 markets and 12 trading systems is 4.13% and statistically significant at the 10% level. The portfolio Sharpe ratio is 0.53. Overall, it is evident that technical trading rules were profitable in futures markets during the earlier sample period, even on a risk-adjusted basis.

Table 4 presents the replication results for the new set of data from 1985 through 2003. During this later sample period the profitability of technical trading rules declined sharply across all 12 futures markets compared to the earlier sample period. Technical trading strategies make statistically significant profits only in two markets, the mark and treasury-bills. For the mark, the REF system generates an annual mean net return of 4.10% with a Sharpe ratio of 0.38, and for treasury-bills the ALX, PAR, and DRP systems generate annual mean net returns of 0.69%, 0.47%, and 0.44% with Sharpe ratios of 0.56, 0.39, and 0.42, respectively. The poor performance of individual trading systems results in statistically insignificant positive portfolio returns for both the mark (1.85%) and treasury-bills (0.17%) and negative returns for the rest of 10 markets. Note that the mark and treasury-bills have shorter out-of-sample periods, which are

1985-1998 and 1985-1996, respectively. In addition, no trading system earns positive net returns for the portfolio of 12 futures markets. As a result, the portfolio annual mean net return across the 12 markets and 12 trading systems drops to -5.82%.

To investigate whether the drop in trading rule profits is related to the assumptions for transaction costs, all 12 trading systems are re-simulated with lower transaction costs of $75 for the 1985-94 period and $50 for the 1995-2003 period.[13] Results show that trading returns for a portfolio of 12 trading systems are still negative for all but the financial markets (0.18% for the pound, 2.36% for the mark, and 0.23% for treasury-bills), although portfolio returns increase slightly across all markets. Moreover, portfolio returns for 3 financial markets are still statistically insignificant. With the lower transaction costs, the portfolio annual mean net return across the 12 markets and 12 trading systems is still only -3.80% and statistically insignificant. Hence, the profitability of technical trading strategies in the earlier and relatively short sample period disappears in the subsequent sample period even with lower transaction costs.

To quantify the decline in profitability of technical trading strategies, the following trend regression is estimated over the full 1978-2003 sample period:

$$(7) \qquad y_{j,t} = \alpha_j + \beta_j x_t + \varepsilon_{j,t},$$

where $y_{j,t}$ is annual mean net returns of portfolio *j* in year *t*, x_t is a time trend, and $\varepsilon_{j,t}$ is an *iid* error term. As shown in table 5, the trend coefficient is negative in 10 of the 12 markets and the negative coefficients are statistically significant in six markets (corn, sugar, silver, pound, mark, and treasury-bills) at the 10% level. Although the trend coefficient is positive for two markets (live cattle and copper), it is insignificantly different from zero in these cases. The size of the decline is economically large in most cases. For example, the estimates for corn show that the annual mean net return across all 12 technical trading systems begins at 4.85% in 1978 and then declines by around 0.70 percentage points each year until 2003. Results for the individual trading systems provide even stronger evidence of decreasing profitability of technical trading strategies. The trend coefficient is significantly negative for all 12 trading systems at the 10% significance level and for 9 systems it is statistically significant at the 1% level. As a result, the portfolio return generated by the 12 trading systems has declined by an average of 0.52 percentage points each year over 1978-2003.

Figure 1 shows the declining pattern of technical trading profitability for the portfolio of 12 futures markets over the entire sample period. A dark bold line in the figure indicates the linear trend. As vividly illustrated in the figure, technical trading strategies performed well in the earlier sample period (1978-1984) and their performance gradually deteriorated during the later sample period (1985-2003).

Summary and Conclusions

Previous empirical studies often find that technical trading strategies are 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 well as profitable trading rules in a trading system. This study addresses the data snooping problem by confirming the results of an original study of technical trading rules and then replicating the procedures on a new body of data. Specifically, to determine whether technical trading rules have been profitable in U.S. futures markets, this paper confirms and replicates a well-known 1988 study by Lukac, Brorsen, and Irwin. The original framework is duplicated as closely as possible by preserving all the trading model assumptions in Lukac, Brorsen, and Irwin's work, such as trading systems, markets, optimization method, out-of-sample verification length, transaction costs, rollover dates, and other important assumptions.

In the confirmation step, the annual portfolio mean gross returns obtained by Lukac, Brorsen, and Irwin (1988) over 1978-1984 were compared to gross returns calculated by applying our trading model to the original optimal parameters. In the replication step, the trading model was applied to a new set of data from 1985-2003. Parameters of each trading system were optimized based on a mean net return criterion and out-of-sample performance was evaluated. Statistical significance of technical trading returns was measured via a stationary bootstrap, which is generally applicable to weekly dependent stationary time series. By minimizing, if not eliminating, the deleterious impacts of data snooping this study provided a true out-of-sample test for the profitability of technical trading rules in U.S. futures markets.

The results confirmed Lukac, Brorsen, and Irwin's original positive findings on profitability. During the earlier out-of-sample period (1978-1984), technical trading rules generated statistically significant economic profits in 6 (corn, lumber, sugar, silver, mark, and treasury-bills) of 12 futures markets. The portfolio annual mean net return across the 12 markets and 12 trading systems was 4.13% and statistically significant at the 10% level. However, the replication results on new data showed that the earlier successful performance of the technical trading rules did not persist in the l985-2003 sample period. Trading systems continued to generate statistically significant profits only for the mark and treasury-bills. As a result, the portfolio annual mean net return across the 12 markets and 12 trading systems dropped to -5.82%. Regression analysis showed that a time trend coefficient was significantly negative for all 12 trading systems at the 10% level, so that the portfolio return generated by the 12 trading systems declined by an average of 0.52 percentage points each year over 1978-2003. In sum, the substantial trading profits in the earlier sample period were no longer available in the subsequent sample period.

There are three possible explanations for the disappearance of technical trading profits in the 1985-2003 period: (1) data snooping biases (or selection bias) in previous studies, (2) structural changes in futures markets, and (3) the inherently self-destructive nature of technical trading strategies. To begin, the results of this study showed that over a relatively long time period U.S. futures markets were informationally efficient at least with respect to past prices. Lukac, Brorsen, and Irwin's (1988) successful finding, therefore, might result from examination of a relatively short and profitable sample period by chance. As noted previously, data snooping problems can occur by searching for profitable in- and out-of-sample periods, trading systems, and trading model assumptions, as well as profitable trading rules. As another explanation, Kidd and Brorsen (2004) report that returns to managed futures funds and commodity trading advisors (CTAs), which predominantly use technical analysis, declined dramatically in the 1990s. The decrease in technical trading profits could have been caused by structural changes in markets, such as reduced price volatility and increased kurtosis of daily price returns occurring while markets are closed. Since technical trading strategies make profits by the process of a market shifting to a new equilibrium, there may be fewer opportunities for profitable trading if prices are not volatile. Finally, forecasting methods are likely to be self-destructive (Malkiel 2003; Schwert 2003; Timmermann and Granger 2004). New forecasting models may produce economic profits when first introduced. However, once these models become popular in the industry, their information is likely to be impounded in prices, and thus their initial profitability may disappear. Schwert (2003) finds that a wide variety of market anomalies in the stock market, such as the size effect and value effect, tend to have disappeared after the academic papers that made them famous were published.

Lastly, these findings and conclusions contribute to the ongoing debate within the agricultural economics profession about what should be taught in marketing Extension programs. Schroeder et al. (1998) report that both producers and extension economists believe that pre-harvest hedging and market timing strategies exist that allow producers to increase prices received. The results of the present study do not support this view if it is based upon technical trading systems. More generally, the results cast doubt on the usefulness of including material on technical trading systems in marketing Extension programs. Since this study directly examined only technical trading systems, it is possible that other forms of technical analysis, such as chart patterns, gaps, retracements, and reversals, may still be useful to producers in their marketing decisions. Nonetheless, the evidence provided by this study suggests a great deal of caution should be used in presenting to farmers any form of technical analysis as an effective method of predicting price movements.

Endnotes

[1] Some technical methods also incorporate volume and open interest indicators.

[2] Park and Irwin (2004) report that among over 90 technical trading studies that have been published since the mid-1980s, about two-thirds show results in favor of technical analysis.

[3] P_t may differ depending on the execution price of a trade. It could be today's closing price, tomorrow's open price, or a daily stop.

[4] There are also miscellaneous fees, such as the clearing fee, exchange fee, and floor brokerage fee, imposed by exchanges. However, these fees are negligible, totaling of approximately $2 per contract (Wang, Yau, and Baptiste 1997).

[5] Note that there is another component of transaction costs that is not reflected in the bid-ask spread: market-impact (or price-impact) effects. Market-impact arises in the form of price concessions for large trades and its magnitude depends on market depth, which is defined as the maximum number of shares that can be traded within a given price range. In general, when a market is tight (wide bid-ask spread), it lacks depth (Engle and Lange 2001).

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

[7] We thank Wade Brorsen for providing us with the formula.

[8] We use Lukac, Brorsen, and Irwin's original results as reported in their 1990 book. This book contains the same results as reported in their 1988 study with more details, including optimal parameters for each trading system and performance in each sample year.

[9] Note that the 3 financial contracts have 5-year out-of-sample periods and the other 9 contracts have 7-year out-of-sample periods. Annual net returns of the LSO system are not included in the calculation of correlation coefficients because Lukac, Brorsen, and Irwin misspecified values of the second parameter (reference interval), which must not exceed values of the first parameter (price channel).

[10] The 858 cases are derived from the following calculation: [3 (financial markets) $\times$ 5 (sample years) $\times$ 11 (trading systems)] + [9 (the rest of markets) $\times$ 7 (sample years) $\times$ 11 (trading systems)]. The LSO system is not counted due to the same reason cited in footnote 8.

[11] Statistical tests using the stationary bootstrap appear to be slightly more conservative than those using conventional *t*-tests. The results of *t*-tests are available from the authors upon request.

[12] Results of statistical tests for the portfolio are insensitive to bootstrap smoothing parameters over 0.8.

[13] These results are available from the authors upon request.

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Table 1. 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
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

Note: Time of trading denotes 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 denotes that a stop order was assumed to be given to a broker and the order exercised at the stop price; Close/Stop denotes that every market entrance (exit) is made at today's closing price (stop).

Table 2. Comparison of Annual Portfolio Mean Returns, 1978-1984[a]

Trading Systems	Lukac, Brorsen, and Irwin's Original Results[b] (1) Gross Returns	(2) Net Returns	(3) Transaction Costs	When Applying the Trading Model of This Study to Lukac, Brorsen, and Irwin's Optimal Parameters[c] (4) Gross Returns	(5) Net Returns	(6) Transaction Costs	When Using Optimal Parameters Identified by Applying the Trading Model of This Study (7) Gross Returns	(8) Net Returns	(9) Transaction Costs
Simple Moving Average with % Price Band (MAB)	-27.5	-60.5	33.0	26.7	11.5	15.2	42.5	27.2	15.3
Dual Moving Average Crossover (DMC)	49.7	22.7	27.0	43.3	27.0	16.3	37.6	18.2	19.4
Outside Price Channel (CHL)	65.4	33.4	32.0	18.5	3.6	14.9	18.5	3.6	14.9
L-S-O Price Channel (LSO)	-0.3	-31.3	31.0	38.7	19.6	19.1	38.7	19.6	19.1
M-II Price Channel (MII)	65.2	25.2	40.0	38.0	14.7	23.3	47.8	25.9	21.9
Directional Indicator (DRI)	-16.9	-55.9	39.0	20.1	13.3	6.8	30.1	16.9	13.3
Range Quotient (RNQ)	-36.2	-79.2	43.0	36.9	12.4	24.5	33.3	8.7	24.5
Reference Deviation (REF)	-0.4	-28.4	28.0	39.2	24.8	14.4	35.4	21.8	13.6
Directional Movement (DRM)	53.8	12.8	41.0	51.6	26.4	25.2	65.6	43.7	21.9
Alexander's Filter Rule (ALX)	45.9	12.9	33.0	13.8	-1.8	15.5	43.5	29.0	14.6
Parabolic Time/Price (PAR)	59.5	3.5	56.0	46.7	13.3	33.4	55.7	22.8	32.9
Directional Parabolic (DRP)	79.9	31.9	48.0	56.2	27.3	28.9	58.0	31.2	26.8
Average	28.2	-9.4	37.6	35.8	16.0	19.8	42.2	22.4	19.9

[a] Continuously compounded returns obtained from the trading model of this study are converted into returns calculated by the total investment method in Lukac, Brorsen, and Irwin's trading model. Returns based on the total investment method can be approximated by multiplying continuously compounded returns by 60 for treasury-bills, 6 for currencies, and 3 for other contracts.

[b] These results are found in table 5 in Lukac, Brorsen, and Irwin (1990, p. 17).

[c] As a few exceptions, performance measures for the CHL and LSO systems are estimated using optimal parameters identified by this study, because Lukac, Brorsen, and Irwin used a different version of the CHL system and misspecified parameters in the LSO system. Also, several optimal parameters of the ALX system in Lukac, Brorsen, and Irwin's (1990, p. 58) results have values that go beyond the parameter range of the system. For example, the optimal parameter of the ALX system for sugar in 1978 was 24%, even though Lukac, Brorsen, and Irwin considered parameters ranging from 1% to 20%. These incorrect parameters are replaced with optimal parameters of this study.

Table 3. The Performance of 12 Technical Trading Systems, 1978-1984[a]

						Trading System[b]								
Market		MAB	DMC	CHL	LSO	MII	DRI	RNQ	REF	DRM	ALX	PAR	DRP	Portfolio
Corn	Net Return[c]	5.22	6.66	1.71	8.44*	8.81*	9.76**	7.03*	7.36	7.65	6.72	-11.69	-4.61	4.42
	Sharpe Ratio	0.33	0.39	0.11	0.52	0.51	0.64	0.47	0.48	0.45	0.42	-0.69	-0.30	0.34
Soybeans	Net Return	6.95	8.27	-5.59	1.58	3.20	1.35	0.67	1.10	7.13	0.95	-2.84	6.69	2.45
	Sharpe Ratio	0.33	0.36	-0.26	0.07	0.14	0.06	0.03	0.05	0.31	0.05	-0.12	0.36	0.14
Live Cattle	Net Return	-2.93	-7.14	-1.14	-6.67	-6.30	-5.10	-7.87	-5.58	-4.41	-6.91	-17.79	-8.97	-6.73
	Sharpe Ratio	-0.20	-0.39	-0.07	-0.40	-0.34	-0.36	-0.49	-0.33	-0.24	-0.39	-0.95	-0.55	-0.54
Pork Bellies	Net Return	-4.87	-7.79	-19.73	-8.40	-13.86	-0.01	-15.72	1.91	1.78	-1.43	5.06	8.44	-4.55
	Sharpe Ratio	-0.16	-0.22	-0.61	-0.27	-0.39	0.00	-0.52	0.06	0.05	-0.04	0.14	0.26	-0.19
Lumber	Net Return	9.23	15.34*	5.99	15.46**	15.63*	15.81**	14.09**	7.30	0.73	-5.12	-8.48	-0.26	7.14
	Sharpe Ratio	0.42	0.60	0.27	0.65	0.61	0.77	0.63	0.31	0.03	-0.22	-0.33	-0.01	0.41
Cocoa	Net Return	4.76	-2.15	8.42	-15.70	6.09	-6.28	-3.20	-1.86	6.85	-6.36	-14.32	3.87	-1.66
	Sharpe Ratio	0.17	-0.07	0.31	-0.57	0.20	-0.27	-0.13	-0.07	0.23	-0.22	-0.48	0.15	-0.08
Sugar (world)	Net Return	9.89	17.69	20.80	21.25	38.40**	17.58	21.72*	19.48	49.66***	25.00*	20.15	32.10**	24.48**
	Sharpe Ratio	0.24	0.40	0.50	0.49	0.85	0.45	0.54	0.45	1.10	0.56	0.46	0.89	0.74
Copper	Net Return	-13.38	-26.42	-14.22	-14.42	-10.88	-9.96	-21.21	-0.33	-6.37	-17.97	-5.46	-12.87	-12.79
	Sharpe Ratio	-0.66	-0.97	-0.59	-0.59	-0.40	-0.61	-0.92	-0.01	-0.23	-0.70	-0.20	-0.52	-0.73
Silver	Net Return	19.75	18.31	0.88	19.39	18.34	12.63	3.32	22.66	15.34	50.06***	49.13***	29.94**	21.65*
	Sharpe Ratio	0.60	0.51	0.03	0.56	0.51	0.37	0.09	0.65	0.43	1.44	1.38	0.96	0.80
Pound	Net Return	1.71	4.74	2.03	4.40	4.08	3.84	4.55	4.75	4.61	-4.11	4.87	2.20	3.14
	Sharpe Ratio	0.17	0.44	0.21	0.44	0.38	0.38	0.44	0.45	0.43	-0.38	0.46	0.23	0.39
Mark	Net Return	9.64**	7.90*	4.51	2.96	11.58***	9.56**	7.65*	6.94*	11.40**	3.63	8.03*	7.88*	7.64**
	Sharpe Ratio	0.91	0.74	0.46	0.31	1.07	0.98	0.73	0.67	1.06	0.34	0.76	0.78	0.97
Treasury-bills	Net Return	3.66**	1.61	0.30	2.65*	1.15	0.42	0.96	0.46	4.88***	4.51**	4.05**	3.78**	2.37**
	Sharpe Ratio	0.92	0.38	0.07	0.76	0.27	0.12	0.25	0.11	1.15	1.07	0.97	0.93	0.76
Portfolio	Net Return	4.23	3.48	0.46	3.09	6.42*	4.35*	1.09	6.04*	8.09**	4.58	2.24	5.52**	4.13*
	Sharpe Ratio	0.44	0.36	0.05	0.33	0.58	0.50	0.12	0.59	0.76	0.48	0.21	0.67	0.53

[a] The sample period for financials (pound, mark, and treasury-bills) is 1980-1984.

[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; PAR: Parabolic Time/Price; DRP: Directional Parabolic

[c] Net Return denotes the annual mean net return (%).

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Statistical tests are conducted using the stationary bootstrap procedure with 1,000 bootstrap resamples and a bootstrap smoothing parameter of 0.1 for individual trading systems and the portfolio of 12 trading systems. For the portfolio of 12 markets, a bootstrap smoothing parameter of 1 is used.

Table 4. The Performance of 12 Technical Trading Systems, 1985-2003[a]

		Trading System[b]												
Market		MAB	DMC	CHL	LSO	MII	DRI	RNQ	REF	DRM	ALX	PAR	DRP	Portfolio
Corn	Net Return[c]	-5.30	-5.44	-3.80	-8.59	-12.34	-5.95	-6.25	-5.08	-11.73	-6.15	-12.28	-11.44	-7.86
	Sharpe Ratio	-0.34	-0.28	-0.21	-0.48	-0.62	-0.37	-0.42	-0.27	-0.59	-0.32	-0.62	-0.65	-0.59
Soybeans	Net Return	-8.54	-4.89	-7.05	-11.64	-8.11	-4.21	-8.72	-1.58	-5.13	-5.58	-11.35	-9.02	-7.15
	Sharpe Ratio	-0.64	-0.25	-0.38	-0.67	-0.41	-0.28	-0.55	-0.08	-0.26	-0.30	-0.57	-0.50	-0.57
Live Cattle	Net Return	-0.85	-5.20	-2.95	-1.99	-6.30	-0.20	0.53	0.06	-4.45	-1.92	-9.26	-6.89	-3.28
	Sharpe Ratio	-0.10	-0.38	-0.24	-0.16	-0.45	-0.02	0.05	0.01	-0.32	-0.18	-0.67	-0.59	-0.38
Pork Bellies	Net Return	-8.99	-11.18	-9.94	-8.52	-3.81	-2.00	-8.12	2.12	-17.23	-10.04	-10.47	-12.08	-8.35
	Sharpe Ratio	-0.46	-0.33	-0.33	-0.27	-0.11	-0.08	-0.32	0.07	-0.51	-0.30	-0.31	-0.38	-0.39
Lumber	Net Return	-5.06	-12.01	-5.70	-3.55	2.25	-3.25	-2.42	-0.10	3.85	-14.81	2.10	2.26	-3.04
	Sharpe Ratio	-0.24	-0.47	-0.24	-0.15	0.09	-0.15	-0.11	0.00	0.15	-0.60	0.08	0.09	-0.17
Cocoa	Net Return	-12.06	-18.73	-26.71	-9.28	-13.11	-0.03	-4.24	-7.06	-21.30	-10.95	-21.28	-16.95	-13.48
	Sharpe Ratio	-0.89	-0.65	-1.02	-0.35	-0.45	0.00	-0.31	-0.27	-0.73	-0.39	-0.74	-0.67	-0.83
Sugar (world)	Net Return	-4.96	-12.26	-13.46	-10.66	-17.29	-3.43	-8.87	-12.39	-13.30	-7.08	-9.60	-6.16	-9.96
	Sharpe Ratio	-0.16	-0.35	-0.42	-0.32	-0.48	-0.13	-0.30	-0.39	-0.37	-0.21	-0.28	-0.20	-0.40
Copper	Net Return	-2.55	-7.04	-10.27	-2.48	0.27	-2.70	2.18	-0.23	-4.50	-2.82	-7.27	-7.44	-3.74
	Sharpe Ratio	-0.14	-0.30	-0.52	-0.11	0.01	-0.14	0.11	-0.01	-0.19	-0.13	-0.31	-0.36	-0.25
Silver	Net Return	-8.24	-11.57	-13.14	-13.10	-15.59	-7.82	-8.17	-4.20	-13.03	-8.21	-9.27	-8.36	-10.06
	Sharpe Ratio	-0.59	-0.49	-0.63	-0.64	-0.65	-0.49	-0.56	-0.19	-0.54	-0.35	-0.39	-0.40	-0.71
Pound	Net Return	0.24	-1.20	-1.72	-0.24	-0.43	-0.63	-1.27	0.19	0.87	1.69	-0.70	-0.34	-0.30
	Sharpe Ratio	0.03	-0.11	-0.18	-0.03	-0.04	-0.07	-0.14	0.02	0.08	0.17	-0.07	-0.04	-0.04
Mark	Net Return	2.90	1.35	2.69	0.51	1.52	0.61	0.77	4.10*	2.24	1.68	1.03	2.83	1.85
	Sharpe Ratio	0.30	0.12	0.26	0.05	0.13	0.06	0.07	0.38	0.19	0.16	0.09	0.29	0.23
Treasury-bills	Net Return	0.09	0.14	0.06	-0.02	-0.32	0.08	0.26	0.05	0.11	0.69**	0.47*	0.44*	0.17
	Sharpe Ratio	0.08	0.11	0.05	-0.02	-0.25	0.07	0.22	0.04	0.09	0.56	0.39	0.42	0.19
Portfolio	Net Return	-4.89	-7.79	-8.08	-6.21	-6.57	-2.68	-4.00	-2.34	-7.42	-5.59	-7.80	-6.47	-5.82
	Sharpe Ratio	-0.94	-1.11	-1.23	-0.85	-0.81	-0.45	-0.68	-0.34	-0.92	-0.71	-0.93	-0.89	-1.06

[a] The sample periods for financials differ: 1985-1998 for the mark and 1985-1996 for treasury-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; PAR: Parabolic Time/Price; DRP: Directional Parabolic

[c] Net Return denotes the annual mean net return (%).

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Statistical tests are conducted using the stationary bootstrap procedure with 1,000 bootstrap resamples and a bootstrap smoothing parameter of 0.1 for individual trading systems and the portfolio of 12 trading systems. For the portfolio of 12 markets, a bootstrap smoothing parameter of 1 is used.

Table 5. Time Trend Regression Results for Portfolio Technical Trading Net Returns by Market and Trading System, 1978-2003

	Regression Estimates				
	$\hat{\alpha}$	t_α	$\hat{\beta}$	t_β	R^2
Markets					
Corn	4.85	0.87	-0.70	-1.94	0.14
Soybeans	-1.24	-0.28	-0.25	-0.84	0.03
Live Cattle	-7.90	-2.38	0.27	1.27	0.06
Pork Bellies	-1.82	-0.24	-0.41	-0.84	0.03
Lumber	4.56	0.63	-0.36	-0.76	0.02
Cocoa	-6.27	-0.98	-0.30	-0.72	0.02
Sugar (world)	23.84	3.18	-1.82	-3.74	0.37
Copper	-10.35	-1.48	0.31	0.68	0.02
Silver	17.93	1.57	-1.44	-1.95	0.14
Pound	4.99	1.64	-0.37	-1.72	0.12
Mark	9.75	3.49	-0.64	-2.60	0.28
Treasury-bills	2.74	2.79	-0.21	-2.23	0.25
Trading Systems					
Simple Moving Average with % Price Band (MAB)	5.09	3.25	-0.56	-5.50	0.56
Dual Moving Average Crossover (DMC)	3.12	1.44	-0.58	-4.16	0.42
Outside Price Channel (CHL)	-1.05	-0.39	-0.35	-2.00	0.14
L-S-O Price Channel (LSO)	3.29	1.27	-0.52	-3.10	0.29
M-II Price Channel (MII)	6.26	2.11	-0.69	-3.60	0.35
Directional Indicator (DRI)	4.93	2.26	-0.42	-3.00	0.27
Range Quotient (RNQ)	1.39	0.52	-0.30	-1.73	0.11
Reference Deviation (REF)	7.50	3.14	-0.56	-3.63	0.35
Directional Movement (DRM)	6.13	1.92	-0.69	-3.36	0.32
Alexander's Filter Rule (ALX)	4.43	1.35	-0.54	-2.53	0.21
Parabolic Time/Price (PAR)	1.64	0.65	-0.50	-3.07	0.28
Directional Parabolic (DRP)	3.66	1.55	-0.51	-3.34	0.32
Portfolio	3.87	2.45	-0.52	-5.08	0.52

Note: The third and fifth columns indicate *t*-statistics for $H_0 : \alpha_j = 0$ and $H_0 : \beta_j = 0$, respectively.

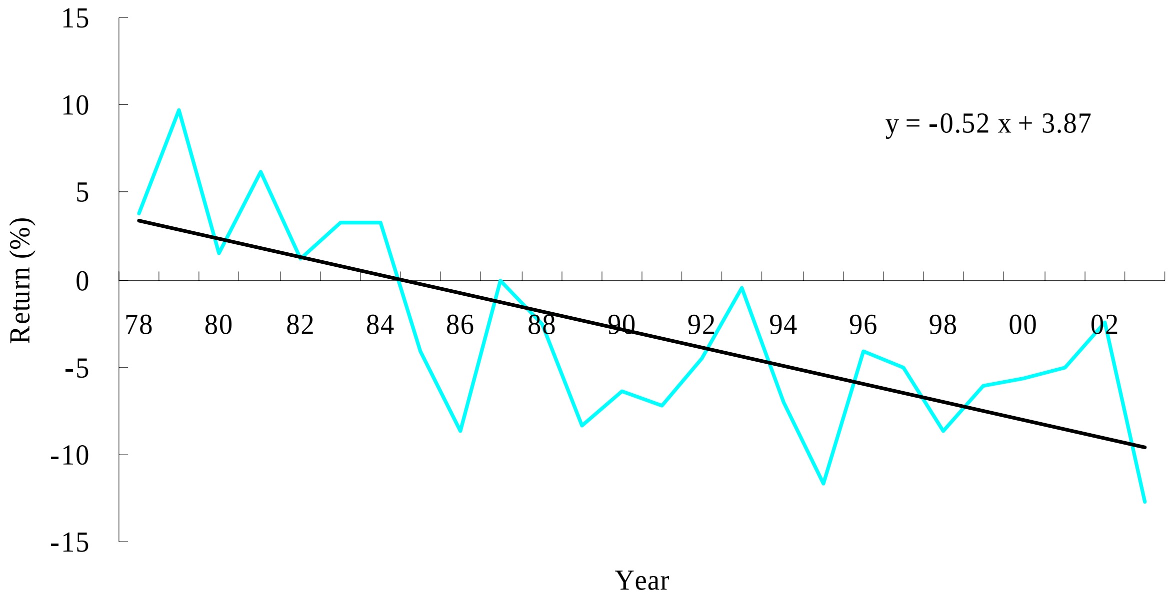

Figure 1. Portfolio annual mean net returns for an equally-weighted portfolio of 12 futures markets using 12 technical trading systems, 1978-2003