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Forecasting live hog futures using technical analysis

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CHAPTER 1
INTRODUCTION

Technical analysis as a forecasting tool for futures prices has been widely criticized and, in some cases, supported in the academic literature. It is in common use by the public, being frequently cited in the press and in market commentaries as having some short term impact on future price movements. It is often provided as a market analysis tool by market quotation services such as Data Transmission Network, Farm Broadcast Partners and other vendors. Publications like *Technical Analysis of Stocks and Commodities* and *Futures* offer regular articles on the use of technical analysis in forecasting prices. Market advisory services frequently cite technical indicators when giving clients marketing advice. Many college courses in agricultural marketing at least provide an introduction to technical analysis. It is a large component of the market analysis done by many large commodity trading funds. Certainly it impacts both speculative and hedging decisions by many participants in the commodity futures markets. If technical analysis has no value, many of the resources dedicated to market analysis are wasted.

This research investigates the effectiveness of four technical indicators of futures price direction applied to the live hog futures market at the Chicago Mercantile Exchange for the period 1987 to 1992. The types of indicators used are a Relative Strength Index (RSI), a Directional Movement Index (DMI) and a Dual Moving Average (DMA). Detailed explanations of these technical analysis methods are provided in chapters 4-7. The DMI and DMA methods assume that prices are trending. Both attempt to identify the direction of a price trend and assume that the identified trend will continue. In contrast, the RSI is often used as a predictor of market turning points. In this conventional role for RSI, prices are assumed to oscillate between relatively high and relatively low values and the RSI indicates an "overbought" or "oversold" condition if its value is relatively high or low respectively. Used in this way, a change of price in the opposite direction is assumed if the RSI is at extreme values. (e.g., rapidly rising prices will generate a high RSI that would be interpreted as portending a correction towards lower prices in the future). But, RSI could also be a trend indicator since it reflects recent directional price movement. The two different uses of RSI will be distinguished by calling the conventional RSI, operating under the standard assumption of oscillating price, ORSI. The less standard use of RSI as a trend indicator will be referred to a TRSI. In both ORSI and TRSI, higher trending prices generate higher RSI values and lower trending prices produce lower RSI values, but the basic underlying assumption about future price direction differs. With TRSI, it is assumed price trends continue, while ORSI assumes price trends reverse in the future.

Of these four methods of technical analysis investigated here, only ORSI operates under the assumption that prices oscillate, while the other three, (TRSI, DMI and DMA), assume that prices trend. Efficient market theory suggests that none of them will be effective if the market is weak form efficient, reflecting past publicly available price information, on which all of them depend. If the market is efficient with respect to past prices, there is no reason to expect the market to go either up or down in the future, based on the information contained in those prices. While some technical analysis methods may use other market information like volume and open interest figures, the four methods investigated here (ORSI, TRSI, DMI and DMA) depend only on past price information that is readily available from the Chicago Mercantile Exchange, brokers, newspapers, radio, television and electronic data information vendors.

The efficient markets hypothesis (EMH) as formalized by Fama (1970) and explained by Marshall (1989) refers to a market's efficiency defined basically in terms of the speed and accuracy with which new information is processed into price changes. The current price should accurately reflect current information, and subsequent price changes should be random, since all current information is "used up", including its ability to predict future new information shocks. According to this hypothesis, the market is considered efficient with respect to a particular class of information. In the weak form, the market is efficient with respect to all past price history including volume and open interest information. With the semi-strong form, the market is efficient with respect to all public information. Public information would include past market price information but also other types of information that might be regarded as available to all market participants. With respect to the hog futures market, U.S.D.A. quarterly hog and pig reports, estimated slaughter rates, cold storage reports, reports of wholesale pork movement as well as other supply and demand information, including information on pork substitutes like beef and chicken, would all be considered public information. In the strong form, the market is efficient with respect to even proprietary information. An example of proprietary information in live hog futures would be the private knowledge of an impending export deal of pork to Russia. This private information regarding demand for pork and subsequently live hogs and live hog futures might be expected to affect expectations of market participants regarding future price levels and thus price itself, were the information public. If the possessors of this type of private information could not use it to profit in the market, then the market would be considered strong form efficient.

If subsequent price changes are random with respect to a particular current class of information, it will be impossible to predict price with that class of information in order to make a profit in the market. Jensen (1978) modified the concept of efficiency, proposing that a market should be considered efficient if information could not be used to forecast price to the extent that profits exceeded transaction costs.

The implications of the EMH on this study and price forecasting in general are clear. If the live hog futures market is weak form efficient, then TRSI, ORSI, DMI and DMA forecasting methods should be unable to produce profits when trading the futures market. The resources currently being spent on generating the technical analysis results are wasted, and market decisions based on the methods will not lead to improved profits. If any of these four trading systems, or any other system based on past price can generate profits, the futures market is not weak form efficient. If that market is weak form inefficient, then it is also semi-strong and strong form inefficient, since the weak form is a subset of the other two. With respect to futures market efficiency in general, Marshall (1989, p. 265) states: "Despite the theoretical appeal of the efficient markets hypothesis, it seems clear that the empirical evidence does not uniformly support it. On the other hand, those departures from efficiency that have been detected are either not great, or have been identified by means that are themselves suspect."

The existence of trends or oscillations in futures price series do not prove or disprove the efficiency of the market. Finding a technical system that would generate a profit in a historical price series is not sufficient. The key criteria is whether those patterns can be exploited to produce future profits.

The null hypothesis for this study is that the live hog futures market at the Chicago Mercantile Exchange is weak form efficient, in the sense that profits exceeding transaction costs may not be extracted utilizing past price information. Data for this study consists of Chicago Mercantile Exchange live hog futures prices for the June and December contracts from 1987 to 1992. The price data is broken down into three two year periods of '87-'88, '89-'90, and '91-'92. TRSI, ORSI, DMI and DMA trading methods are tested utilizing nine different combinations of fixed stop loss, trailing stop loss and no stop loss strategies. Each of these combinations is tested over a wide range of values for the technical indicator buy and sell levels. Each general method /stop loss strategy (GTM) is historically optimized in the 1987-1988 time period with regard to buy and sell level. Their out of sample performance is then analyzed for two subsequent two year periods. Two separate historical optimization criteria were utilized, total profit and an index based on the sum of profitable trades for the period and the sum of the losing trades for the period. Profit, maximum draw down, total trades and percent profitable trades are reported for '89-'90 and '91-'92 for the 72 optimized trading rules as well as '87-'92 summary profit results for the 36 GTMs. The correlation of profits for each buy and sell level across time periods is calculated for each of the 36 GTM's as a measure of the feasibility of parameter optimization, as use of historically optimized trading strategies assumes that correlation of profits across time periods is positive. In addition, the sample mean profit and sample standard deviation of profit for each GTM is calculated for the entire 1987 to 1992 period, as well as a z score to test whether the mean profit is statistically greater than zero.

Possible sources of inefficiency in the market that might support the feasibility of technical analysis used in this study will be discussed in chapter 2. Chapter 3 will discuss general research procedures and methods used in this study. Individual chapters discussing each of the four technical analysis methods follow, where the calculation of the indicator and individual test results are presented. Finally, the overall findings of this study and its implications are considered.

CHAPTER 2
REVIEW OF THE LITERATURE

If the efficient markets hypothesis is correct, there should be no exploitable trends in a market price series. Delong et al. (1990) proposed that a positive feedback model might explain price behavior (and allow for the presence of a trend in price). In this model, rational speculators buy ahead of noise demand knowing that there are "noise traders" who will buy on market strength and sell on market weakness, irrespective of market fundamental supply and demand information. This noise demand could be caused by traders using technical trend following systems, execution of stop loss or market orders around round numbers or technically obvious prices such as old highs and lows or the liquidation of positions due to margin calls on large price movements. A "follow the herd" mentality and the lack of immediate arbitrage by rational investors on the basis of fundamental information might be explained by risk aversion for the short term. When the stock market crashed in 1987, there was no obvious change in market information that might have caused a drop in stock prices of 20% in one day. That would appear to be an example of positive feedback behavior in prices. The rational use of information external to the market might have implied buying any small dip immediately, yet information from the market itself may have prevented this immediate arbitrage. A fear that the market knew something that the individual trader did not, and outright fear and panic might have changed an individual's perception of the distribution of price given the information available. This type of behavior makes more plausible the existence of a trend exploitable by technical analysis, or the existence of an "overbought" or "oversold" condition exploitable by an RSI used as an oscillator- depending on the length of time that the positive feedback behavior influences prices. The concept of being "overbought" or "oversold" implies a reversal in trend to an equilibrium price in the future. Predicting a continuation of trend implies that price has not reached an equilibrium based on the information that is known today. Neither idea fits with the immediate arbitrage assumed with an informationally efficient market.

Romer (1993) suggested that individual investors may have uncertainty about the quality of information possessed by others. They may look to the actions of other investors to adjust their own perception of value. Also, because of a great dispersion of information among investors, the individual incentive to trade on that information may be small due to transaction costs. In either case, the individual chooses not to trade immediately. Romer's theory allows for the rational use of information, but the full extent of the information is revealed by the market's action rather than being immediately reflected in price. Under this scenario, if a market failed to respond to negative fundamental news, an individual trader might conclude that other traders had better quality information of a positive nature and thus adjust his valuation according to the trading behavior of the market. In this case the positive news would be reflected over time in price rather than immediately and could account for some trend in price in the absence of new news. Either the positive feedback/noise model or Romer's model could account for the presence of an exploitable trend in an otherwise efficient market and thus allow for the potential success of price trend forecasting models based on past prices that do not immediately reflect all information.

Ma, Rao and Sears (1989) conducted a study on the effect of price limits on futures prices. The study indicated decreased volatility of futures prices in the presence of limits, which is consistent with futures prices overreacting to information at times, in the absence of limits. If prices do overreact, it could result in the overbought and oversold conditions assumed by ORSI. Extended over a long enough time frame, overreaction could also be expected to generate trend patterns. Their study supported the hypothesis that prices may overshoot fundamental value at times.

Futures contract price series are relatively short in length and suffer from liquidity problems in the months distant from contract expiration. The liquidity problems in the beginning of a contract's existence generates concern regarding the assumption of homogeneity within the entire series. Most research using actual price histories limits the use of a contract's life to those months nearer to expiration of the contract. Some previous studies have created a synthetic price series by assuming a distributional form for the actual price series and estimating the required parameters for that distribution from the contract price history. A synthetic price history is then constructed as long in length as desired, utilizing a Monte Carlo simulation technique and the estimated parameters. Brock, Lakonishok and Lebaron (1992) studied technical analysis trading rules used on the historical Dow Jones Stock Index. They utilized various Monte Carlo simulations of price histories and compared them to results using the actual price series. Taylor (1994) explored the profitability of a technical analysis channel rule using currency futures. He rejected a null hypothesis of zero excess returns at the 1 percent significance level and used a Monte Carlo simulation study to explore why the channel rule might generate positive returns. The simulation approach benefits from an increase in the number of observations, but accepts the risk of specification error regarding the process generating the price series.

Another approach has been to use only nearby futures contracts. This avoids liquidity concerns in the distant months of a given contract and the resulting concern regarding homogeneity within an individual contract's lifetime. It limits the degrees of freedom, however, as the contract is only analyzed when it is the contract closest to expiration ("nearby"). To get additional degrees of freedom, the contract is then "rolled over" when it expires, to the next contract month, with the assumption that the two contracts are homogeneous. This creates an artificial contract that is essentially continuous. The contract can also be rolled over prior to expiration to avoid the possibility that the contract may have different distributional characteristics during its delivery period. Combining contiguous contracts creates more observations of price and increases degrees of freedom. Extrapolating results from the "continuous" price series to performance in actual futures markets involves accepting the homogeneity of contiguous contracts and accounting somehow for the additional transactions costs of commissions and slippage that would be required to roll over positions when the nearby futures contract expired in the actual market. Baur (1990) approached the problem of sample period dependency in his study of futures market efficiency by forming such a "continuous" price series. He created an extremely long price series of 53 futures prices and some 13 spread combinations over a period from January 1964 to April

1992. He used this data to investigate whether past extreme returns had the power to predict future returns, and whether a risk premium exists in futures markets. He found evidence of some persistence in returns as well as evidence of a risk premium.

Repeatable profits refute the efficient markets hypothesis by definition. At issue in the profit method of analysis is whether those profits are repeatable. Tomek (1984, p.22) warned of the possible presence of systematic components within a randomly generated price series due to chance. "The speculator clearly should be skeptical of claims that technical analysis of past prices can successfully forecast forthcoming prices." Profitable patterns can be found within historical futures price series. Some futures industry publications carry advertisements for trading systems claiming up to 90% profitable trades in a particular price history. Of course the implication that this performance will carry over into the future is doubtful to say the least. The prices of such systems seem well under the discounted present value of all of the future profits of a 90% successful system. It seems more plausible that the possessor of such a successful system would use it privately, rather than publicizing it and risking the inevitable arbitrage that a relatively efficient (if not totally efficient) market would bring. The key question is how any system will perform in forecasting future prices, not explaining past prices. It has been noted by Granger (1979) and others that publications about trading rules may be biased towards negative conclusions. "If such a (foolproof) strategy were found, it would hardly be made public, even by an academic."

Schwager (1989, 1992) wrote two books entitled <u>The Market Wizards</u> and <u>The New Market Wizards</u>. The futures traders interviewed in these two books claim profits far exceeding in magnitude and consistency what would be expected in an efficient futures market, and Schwager mentions still other traders with remarkable profit records that are not included in these books. The specific trading rules of these traders are not revealed for obvious reasons, but both historical price information and public information are apparently used by most.

Providing anecdotal evidence of market inefficiency, Murphy (1986) conducted a study where he used the performance of large commodity funds as a measure of the effectiveness of technical analysis in the futures markets. While it may be true that these large funds often use technical analysis in taking market positions, they avail themselves of other types of information as well. The exact method of forecasting price naturally remains hidden for these funds, so the assumption that their market performance serves as a proxy for the effectiveness of technical analysis seems to be a rather strong one. Their performance has the advantage of being on public record and on the whole is rather poor so that may be considered a weak vote for market efficiency at some level.

Some studies have shown that smaller traders perform rather poorly. They might be more likely to use past price information because of its low cost and relative ease of use. Large traders and commercial hedgers should have greater resources at their disposal to conduct more costly and complicated forms of analysis such as fundamental supply and demand studies. That some groups of traders fail to consistently generate profits hardly disproves that it is possible to profitably predict prices. Indeed, Schwager's trader case studies provide anecdotal evidence that futures markets are informationally inefficient.

Applying trading rules to actual price histories is not unique to this study, but neither is it a universally used procedure. Another approach used in other research has been to look for statistical patterns in the price series, which then are assumed to be proxies for trading profits if they are sufficiently predictable. Statistical searches for a profitable pattern of non randomness in a price series have utilized tests for serial correlation, runs analysis, filter rules and spectral analysis. Marshall (1989, p. 264) states that the dependencies detected by the serial correlation and runs analysis methods may have a tenuous relationship with profitable mechanical trading rules. He describes filter rules as providing "a check for nonlinear financial type dependencies", and spectral methods as providing "a test in the frequency domain." Sweeney (1986) did a study of filter rules in the foreign exchange market and concluded that, during the period of time studied, there either appeared to be significant speculative profits possible or the presence of a significant time varying risk premium. Decoster, Labys and Mitchel (1992) studied commodity futures prices and found evidence of a chaos system. They found an apparent nonlinear structure to futures prices that was not inconsistent with the deterministic component found in chaos. The conclusion was drawn that there was something beyond heteroscedasticity present in the price structure. They felt that chaos accompanied by noise is probably representative of commodity futures prices. As mentioned in the introduction, the presence of a pattern is only a necessary condition for the presence of a profitable trading rule. A relatively high degree of predictability of the pattern is the sufficient condition. This requires both pattern recognition and trading rule systems to be tested ex post to determine forecast accuracy.

A chief criticism against checking market efficiency by measuring profits using a mechanical system is that results could be due to chance order within an otherwise random set of price changes, and thus not repeatable in future tests. This is a hard claim to refute empirically. 19 out of 20 flips of a supposedly balanced coin coming up heads would not prove conclusively that it was unbalanced, nor would 90% profitable trades over the course of this study conclusively prove that the profits were due to anything other than random chance. A long string of observations would be desired to test the balance of the coin as would a long string of actual trades to test profitability. Additionally, markets may change so that different patterns exist at different times and are exploitable by different trading rules or different parameters for those rules at different times. If the pattern required to be profitable is discernable to a trader and he does change trading rules, as some of the traders interviewed by Schwager seemed to indicate that they had done, the presence of consistent profits would provide evidence of an inefficient market. This study does not attempt to switch technical trading rules based on a discernable pattern. It does seem reasonable to expect the ORSI method to do well when the TRSI, DMI and DMA methods do poorly, and vice versa, because the general data structure required to generate a buy for the ORSI would generate a sell for the other three, irrespective of any predictive power.

There have been a number of academic articles published regarding the profitability of trading systems based on past price information. Pruit, Tse and White (1988,1989,1992 pp. 55-56) did a study of a composite technical analysis based trading system they called CRISMA. It utilized a Relative Strength, Moving Average and a cumulative volume component and generated a risk adjusted return of 6.13% to 35.65% for stocks and 12.05% to 28.72% return per round turn for stock options in the January 1976 to December 1985 period. A subsequent study of the January 1986 through December 1990 period showed a risk adjusted return of 22.28% to 26.45%, before transaction costs. They stated: "We believe a finding of continued success for the CRISMA system would provide important and convincing new evidence concerning the (in)efficiency of the securities markets and the ability of investors to "beat the market" by employing complex technical trading strategies." Two of the technical analysis components used in their study on stocks and options are evaluated in this live hog futures study- a relative strength and moving average indicator.

Irwin and Uhrig (1984) did a study where they evaluated 4 technical trading systems over 8 different commodities with all of the systems showing substantial profits for the 1961 to 1981 period. Live hog futures were among one of the futures markets analyzed utilizing a channel system, moving average, dual moving average and a directional indicator system. Taylor (1985) did a study of futures prices where he studied the autocorrelation in prices and found evidence to reject the random walk hypothesis at the 5% significance level. He stated that "Market efficiency might perhaps be refuted by finding the profit potential of a trading rule based on past prices." He later did a study published in 1992 where filter, channel and moving average technical trading rules were compared to an ARIMA time series forecast for currency futures during the December 1981 to November 1987 time period. All of the trading rules were profitable and the conclusion was drawn that the profits were too large to be explained by a time-varying premium, thus implying inefficient pricing. Nefci and Policano (1984, p. 465) did a study on a moving average and slope method of forecasting futures prices, finding that the moving average had some predictive power in the RMSE sense but that the slope method gave mixed results. They mention "If futures markets are efficient, then the existence of traders who use technical analysis is certainly an anomaly."

Lukac, Brorsen and Irwin (1988) tested 12 different technical trading systems with 12 different commodities from 1978 to 1984. Live hog futures were not considered. Seven of the systems generated significant gross returns while 4 of the systems generated significant net and risk adjusted returns. The authors felt that a disequilibrium model provided a better description of short run futures price movements than did a random walk model. The disequilibrium model allows a slower than instantaneous adjustment to new information shocks due possibly to information costs, transaction costs or risk aversion. Channel systems, momentum oscillators, moving averages and systems with trailing stops were all used in their study.

Lukac and Brorsen (1989, pp. 55-65) did a study on the usefulness of historical optimization of parameters for technical trading systems. This is what the current research attempts to do in the 1987-1988 period for hog futures prices. Lukac and Brorsen looked at optimizing the parameters for a DMI and channel system in 15 markets. A survey in 1987 showed that 15 out of 19 futures fund advisory groups did optimize their technical trading systems based on past prices. Lukac and Brorsen concluded that historical optimization was of limited use with the random selection of parameters performing as well. The current research addresses the optimization problem by tracking out of sample performance of historically selected trading rules, but also by investigating the performance of every parameter set over the whole 6 year period for each technical forecasting method. Lukac and Brorsen do state in their study that "These results reject the random walk for commodity prices." Their two technical systems were significantly profitable over their diversified 15 market portfolio.

Whether the actual forecast methods looked at in this current study are useful is heavily dependent on the efficiency of the market, either in a temporal sense or with respect to the actual market incorporation of information. Somehow, to be useful, the forecasting methods must indicate where the market is going before it gets there. This would imply that the market did not process the forecasting information faster and more correctly than the forecast method, and thus was inefficient. There have been a number of academic studies that challenge the efficient markets hypothesis as the best model available to explain financial market behavior. Many of the alternative models present some theoretical basis for expecting some nonrandomness in future price direction. If using forecasts found optimum in the '87-'88 period out of sample over 4 years shows a substantial profit, it will indicate some degree of market inefficiency as well as provide evidence of the usefulness of the forecast method in making marketing decisions.

This study was directed towards three general objectives:

1. Test whether out of sample profitable trading rules for ORSI, TRSI, DMA, and DMI using nine different stop strategies (36 different GTMs) could be identified using '87-'88 optimization results.
2. Investigate the stability of performance of buy and sell level parameters generally for the 36 GTMs between the three periods of the price data..
3. Determine how well each of the GTMs performed over the entire 1987 to 1992 period.

The first objective is important because the critical concern in choosing a trading technique is choosing one that will work well out of sample. Historical profits or "fit" to the data does not in itself imply any forecasting ability. Traders do not trade GTMs. They trade specific individual trading rules consisting of a rule for when to buy and a rule for when to sell. The first objective was tested in this study by rating all of the '87-'88 period performances for each trading rule within each GTM, choosing the best individual rule for that period, and tracking its performance in 2 subsequent periods, '89-'90 and '91-'92.

The second objective is important because of the limited number of observations obtained from tracking individual trading rule ex post performance while investigating objective one. Tracking the correlation of profits between the three periods '87-'88, '89-'90 and '91-'92 for every individual trading rule within a GTM and averaging those correlations gives a statistic suggesting the amount of period to period stability of performance that might be expected of any individual trading rule within the GTM.

The third objective obtains a broad measure of how well the GTMs fit the entire 1987 to 1992 time period on average. Mean profit and standard deviation of profit provide a means of comparing GTM performance in the historical period.

CHAPTER 3
RESEARCH PROCEDURES

Data

Technical analysis trading rules are applied to actual price histories in the live hog futures market obtained from the Chicago Mercantile Exchange. Individual Turbo Pascal programs test the technical analysis trading methods on the historical data, utilizing an I.B.M. compatible personal computer. Summary output, daily trade records and daily parameter calculations are employed to verify the accuracy of the computer algorithms.

This study utilizes the daily open, high, low and closing prices for the live hog futures contracts at the Chicago Mercantile Exchange expiring in December and June for the period of 1987 to 1992. (DMI uses all 4 daily prices while the other three trading methods use only daily closing and opening prices.) Each contract's price series is truncated to approximately the nine months prior to expiration in deference to concerns over liquidity, and is only traded for approximately 6 months prior to expiration. This results in a series of prices where a contract is available to trade each day the market is open, with the actual contract traded being June for approximately six months, followed by December for six months and alternating thereafter. The technical indicators are calculated starting nine months prior to expiration on each individual contract to allow the longer length parameters time to generate a trading signal by the first day of trading for the contract. Trading using the June contract begins the day following the expiration of the previous December contract, and December is used starting on the day following the expiration of the previous June contract. Homogeneity is assumed within each individual contract, from nine months prior to expiration to the close of the last trading day, and between the June and December contracts. The same trading rules are used on both the June and the December contracts. It is not a continuous price series, as all open trades are closed out at a contract's expiration. If a position is taken the following trading day, it is in the next contract using the technical indicator calculated based on that contract's price series.

This research divides the six years of historical prices into three periods of two years each, '87-'88, '89-'90, and '91-'92. Results are reported by period. It would be desirable to have more years and additional periods, but even this amount of price data generates huge volumes of output. This is primarily due to the fact that each technical analysis method is looked at under nine different stop loss strategies and across a wide range of parameter values.

Procedures and Calculations

All positions are taken or closed out at the opening price of the day following a trading signal, with the exception of an open position on the day of a contract's expiration. Trading signals are always evaluated after the market closes. If a signal indicates a trade, it is always made at the following day's opening price.

A trading buy or sell signal can come from two sources- the technical indicator or a stop loss rule. Once a position is established based on the technical indicator, it will be held until the technical indicator gives a signal to reverse the position, a stop loss rule is triggered to close the position, or the contract expires. If the technical indicator gives a signal in the opposite direction of the current open position, two contracts are traded at the following day's opening price. One contract closes out the current position, and the second contract establishes a new open position in the opposite direction. In the case of a stop loss rule being activated, only one contract is traded at the next day's opening price to close out the existing position. After being stopped out in this fashion or being closed out due to contract expiration, a new technical indicator signal is required to establish a new position. It is possible with an open position that both a stop loss signal and a technical indicator signal are generated simultaneously after the close of the market. In this case, two contracts are traded on the following market's open in the opposite direction from the current position. In effect, the stop loss is executed and a new position is taken simultaneously based on the technical indicator.

Stop losses are calculated for open positions using the closing price of the day and when executed, are done so at the opening price of the following day. Stop loss rules are evaluated for the TRSI, DMI, DMA and ORSI, to more closely replicate real world trading practices. A stop loss rule acknowledges loss aversion on the part of market participants. This study attempts to fit different degrees of loss aversion by the range of the stop loss rules evaluated. At one end of the spectrum is a risk loving market participant who uses no stop loss rule at all. At the other extreme would be someone who did not participate in the futures markets because of the risk involved. Of those individuals inclined to participate, but with some degree of loss aversion, four arbitrary nominal levels of risk are selected with two different methods of calculating the risk. The methods involve a fixed stop and a trailing stop level, each calculated on nominal values of $250, $500, $750 and $1000 per trade. A fixed stop level is calculated by determining the price level for the contract at which an open position, closed out at that price, would sustain the nominal level of loss. This nominal level of loss includes a $90 transaction cost. If the loss calculated at the day's closing price is equal to or exceeds this nominal level, the open position is closed out at the following day's opening price. A fixed stop loss level is "fixed" in the sense that it depends on static values: the initial contract price of the position, the nominal loss level and a transaction cost. Once a position is taken, the price level required to generate a fixed stop loss signal never changes for that position.

A trailing stop loss signal is also executed at the following day's opening price, but the calculation of the price level required to generate the trailing stop loss signal is different. A trailing stop loss models the behavior of a market participant who is more risk averse than the user of the fixed stop. The user of a trailing stop, in effect, marks his position to the market every day with respect to his stop level. Like the fixed stop user, the trader is unwilling to lose more than the nominal value of the trailing stop, ($250, $500, $750 or $1000), but calculates the loss based on lost profits, as well as initial margin. If the market moves in a favorable direction after initiating the trade, the trailing stop price level follows the market in that direction. The price level required to generate a stop loss signal is calculated from either the initial position price, or the most profitable subsequent closing price with respect to the open position. In long positions, the highest closing price after the initial buy price or the initial buy price is used in the calculation of the stop price signal. In short positions, the lowest closing price after the initial selling price or the initial selling price is utilized. In the case of an open long position, a trailing stop of $250 is calculated by the following formula: *max (initial price, subsequent closing prices) - ($250 - $90 transaction costs) = maximum closing price required to generate an at the market sell order on the following open.* A fixed $250 stop for an open short position is calculated by: *initial sell price + ($250 - $90) = minimum closing price required to generate an at the market buy order on the following open.*

The nine variations of stop loss rules allows the four different technical strategies to be tested in a way that mimics how different traders with varying levels of risk aversion might actually use the methods.

The stop loss strategy used in this study evaluates the current day's closing price to generate a signal which is then executed on the following day's open. It was not possible to use intraday prices to calculate the closing price level required to generate a stop loss signal, due to the limitations of the data (open, high, low and close). A fixed stop price could have been calculated but not a trailing stop. The fixed stop requires only the initial trade price and stop loss level to calculate a stop loss price that could be entered as an open stop loss order held over from day to day. The trailing stop loss strategy is more complicated. For the trailing stop loss, the price level required for a signal could potentially change throughout the day if calculated on intraday prices, because of the way the trailing stop follows favorable price movement. The day's possible price range of $1200 ($1.50 cwt. limit x 2) exceeds all of the trailing stop levels. Specific stop price levels could change during the day for all of them if they were calculated on the intraday high or low price. To know whether a trailing stop based on intraday prices has been triggered requires knowing whether a stop level price occurred after the intraday high or low was achieved (if that high or low generates a new stop trigger price). This was not possible with the data used in this study. If trade by trade price information were available, intraday trailing stops could be calculated, but the implementation of that strategy would require the market participant or his broker to closely monitor the market for new stop loss levels throughout the day.

The previous day's high or low could be used in place of its closing price in calculating new trailing stop levels. This would not be unreasonable, but the close was selected because it is often the more recent price level and might better reflect the market equilibrium price. Market efficiency argues for the more recent price. An assumption of market inefficiency may argue for choosing the closing price over the extremes of the day as well. It makes sense to think of fundamental supply and demand traders as longer term in focus and noise traders, if they exist, as short term traders. If noise traders do drive price temporarily away from fundamental value on an intraday basis but tend to cover their positions at the end of the day, the closing price should more closely reflect fundamental value, and be a more reliable choice for calculating market signals. Some market advisory services utilize market close only orders, implying a stronger confidence in the closing price. Following this rationale, previous closing prices are used in this study to calculate trailing stop price levels and current closing prices are used to determine if the stop price has been exceeded.

The decision to close out a trade on the following open was not necessary for the live hog futures market, even assuming that closing price was evaluated for the generation of the stop loss signal. It would have been possible to assume that stop loss orders were executed at the closing price of the day. The Chicago Mercantile Exchange allows a stop, close only order that could have been used for the execution of the stop loss. The stop price level required to be exceeded for the day is always known from the previous day's closing price, so it would be possible to enter a stop, close only order at that specific price. Other exchanges do not allow the placement of this type of order (e.g., the Chicago Board of Trade) and it would be necessary for the market participant or his broker to monitor closing price and place a market order at the close to execute this type of stop strategy in those markets. By adopting the convention of executing stop loss signals on the following open, the stop loss strategy in this study is readily transferable to other contracts at other exchanges, without requiring constant monitoring of the closing prices.

Executing stop loss orders on the following open does allow for considerable slippage (or gain) on big move days, depending on the direction of the move from the previous day's price and the open position. The average difference in price between the previous day's close and the following open, calculated for all days eligible to be traded for this study is very small, only $0.001326 per cwt. or 53 cents in profit or loss. Though small in average effect, the slippage could significantly alter results of small samples.

There are 5 trading days in this study that the opening price is at limit bid or asked from the previous close. On 2 of the 5 days, prices traded 40 cents per cwt. off the limit price during the day so that an assumption that an order is filled at the opening price would seem reasonable. It may be unreasonable to assume slippage of $.025 per cwt. on a trade if the direction of the trade requires the slippage to be applied beyond the daily price limit, but that is not accounted for in the programs used to run the trading simulations. A more serious departure of simulated results from those that would have transpired in the real world is possible on the 3 days where prices opened limit bid or asked and did not move that day. The trading simulation programs assume trade signal execution at the opening price, and since volume of trading is not used in this study, it is unknown whether the assumed trade actually occurred. If it did not, those three days all could have been traded at the following open price, but those prices were $1.27, $1.50 and $1.30 beyond the previous day's locked prices in the direction of the previous day's limit move. The simulation programs do not record if trade signals occured on these three days.

As mentioned previously, Lukac and Brorsen (1989) concluded that historical optimization of technical trading methods was of limited use, with random selection of key parameter values found to be as effective. The strength of any conclusions in the current study regarding an optimum parameter level selected in the '87-'88 period and tested ex post in the periods of '89-'90 and '91-'92 is limited by having only 2 out of sample test periods. Looking at all 72 optimized GTM's provides a number of observations on those 2 out of sample periods, but all of the observations are based on the same underlying price structure. (36 GTM's historically optimized on two separate criteria yields 72 individual trading rules with 2 out of sample periods each).

Two criteria were selected to choose the optimum performing '87-'88 trading rule for a GTM which is then tested out of sample in the '89-90 and '91-'92 periods. One optimization criteria is total profit per time period. The other is an index based on period profit and period loss. Selection is made for the highest profit within the GTM in the first case, and the highest index in the second. The index is computed as follows: *(period's profitable trade sum / greatest period profitable trade sum for GTM) - (period's losing trade sum / most negative period losing trade sum for GTM).* The highest possible index score is 1, attained when the period profit sum for the trading rule equals the maximum for the GTM and the loss sum is zero. The lowest possible index score is -1, when the period profit sum is 0 and the period loss sum equals the most negative period loss sum for the GTM. The index incorporates period losses into a weighting scheme where relative performance with regard to both profit and loss are considered in picking an optimum trading rule.

Maximum drawdown is a measure of risk and capital requirements for a market participant and, as such, is an important result reported in this study. It can be thought of as a rough measure of the capital required (beyond initial margin for one contract) to trade a particular system over the two year period. Using maximum drawdown instead of period cumulative loss as part of the historical index used for optimization was initially considered. It was not included, because like period profit and loss, its inclusion in an index to predict future performance implicitly assumes that past performance will to some degree repeat itself in the future. That assumption may be on somewhat shakier ground with regard to maximum drawdown than it is with period profit and loss. This is because period profit or period loss is not order dependent while maximum drawdown is. A series of profits and losses in any order result in the same sum of profits and same sum of losses for the series. A change in the order dramatically changes the maximum drawdown calculation for the same series. There seems to be no reason to assume that profits and losses should repeat themselves in any type of order in future periods, even if the trading method captures some type of market inefficiency. For this reason, the sum of period losses was chosen as a measure of market risk for the optimization index.

Maximum drawdown is defined as zero or the lowest negative account balance over a 2 year period, whichever is less. The lowest account balance is calculated as if no money is deposited initially in the futures account at the start of the two year period. While initial margin is required to trade futures contracts, it can be met by T-bills and other interest bearing instruments and is not used in the calculation of drawdown here. All open positions are marked to market at the close of each day, with the transaction cost of $90.00 included in the calculation, even though the commission and exchange fees, as well as slippage on the exit of the trade, may not have occurred yet. Since the position is open, they will occur and are accounted for. This calculated value of any open position is added to the running total of profit for the two year period on all previously closed out positions. The maximum drawdown takes on the lowest value of these daily calculations, or zero whichever is less. Profit is calculated from only completed trades.

In addition to using a direct approach of testing the effectiveness of historical optimization with actual optimized trading rules used out of sample, a simple correlation of profits across time periods is calculated for all individual buy and sell level combinations investigated. It provides an objective measure of how stable the performance of the parameter combinations are, taken as a whole, and provides an extension to Lukac and Brorsen's study. Individual period profit for each buy/sell level combination is taken to be an element in a vector of profits for a particular GTM for that period. The simple correlation of the elements of these vectors between periods yields a crude measure of the stability of parameter performance. Correlation coefficients near 0 support Lukac and Brorsen's findings that historical optimization of parameters is of questionable value. Since the historical optimizations used in this study select for high profits in the historical period, positive correlation coefficients greater than 0 tend to support historical optimization. A finding of a negative coefficient might suggest that choosing an optimum parameter combination based on poor profit performance in the preceding historical period should be considered.

Profits are calculated with an adjustment for transaction costs. Those costs are estimated to be constant at $90.00 per round turn, consisting of $70.00 in commission and exchange fees, as well as slippage of \$.025 per cwt. when entering the trade and \$.025 per cwt. when exiting. (\$.025 per cwt. is the minimum price movement in live hog futures, equaling \$10.00 on a 40,000 pound contract).

If market prices are determined by an efficient process, profits would not be expected to be consistent from one period to the next, as the future price direction would be the result of a random process. Given enough observations, the expected result would be a loss of the transaction costs in an efficient market.

Summary Tables

The following chapters are devoted individually to ORSI, TRSI, DMA and DMI. The same summary table format is used in each chapter. The out of sample summary table for trading rules selected on the basis of historical profit, and the table for those rules selected on the basis of a calculated index represent the out of sample period results for an individual trading rule selected for each stop loss strategy within the general technical analysis method. Both the period correlation table and the mean profit, standard deviation and z score table represent all of the individual trading rules within a given stop loss strategy / technical analysis method. Both of the latter tables are intended to give an overall picture of a particular method of technical analysis complemented by a particular stop loss strategy, while the out of sample tables represent specific trading rules within the general methods and stop loss strategies.

The z score presented in the last column of the last table in chapters 4-7 is calculated to test the null hypothesis that the 2 year population mean for a particular technical analysis method / stop loss strategy is equal to zero. The alternative hypothesis is that the true mean profit is greater than zero and the test is conducted at the 5% significance level. The z score is calculated as: *(sample mean - 0) / (sample standard deviation / square root of # of observed GTM 2 year profits)*. Since the number of observations of 2 year profits always greatly exceeded 1,000 for each GTM, the sampling distribution of the mean is assumed to be approximately normal and the critical value required to reject the null hypothesis was found to be 1.645 obtained from a standard normal table. Any time the z score exceeded 1.645 for a GTM, the null hypothesis is rejected at the 5% significance level and the alternative hypothesis accepted that the true mean profit for the GTM is greater than zero.

CHAPTER 4
OSCILLATING RELATIVE STRENGTH INDEX

Procedure

The ORSI trading method, like all technical analysis trading methods, is based on past price information. ORSI is what is commonly called the Relative Strength Index or RSI by users of technical analysis. It is referred to as ORSI in this study to remind the reader that it depends on the theory of oscillating prices and to distinguish it from TRSI, which is a less conventional method of using the same RSI statistic as an indicator of trending prices. In this study, daily closing prices were used to compute the RSI statistic for both ORSI and TRSI. It was computed for 27 different day lengths, from 4 to 30, using the following method of computation. The difference between the current closing price and the previous day's close (Pricediff) was calculated for each contract's 9 month price history prior to expiration. Then, using an N day length parameter, the positive Pricediff variables over the previous N days (including the current day) were summed in a PosSum variable for the current day. The same thing was done for the negative Pricediff variables which were summed in a NegSum variable for the current day. The current day's RSI was then calculated by: *[PosSum / (PosSum + abs(NegSum))] * 100*. RSI ranges in value from 0 to 100 (0 when all of the N days price changes have been negative and 100 when all of them have been positive). Because there were 9 months of price data for each hog futures contract, there were an adequate number of observations to compute the longest RSI prior to the contract being considered eligible to trade, which began approximately 6 months prior to expiration. A day's RSI is assumed to be calculated after the close of trading and includes the price difference between the close of the current day and the previous day.

The proportion of dollar changes up in value to the total dollar changes both up and down, measured from close to close over the previous N-1 days plus the current day, is what determines the level of RSI. Strong up trending prices generate high RSI values, while strong down trending prices generate low RSI values as demonstrated in Figure 4.1.

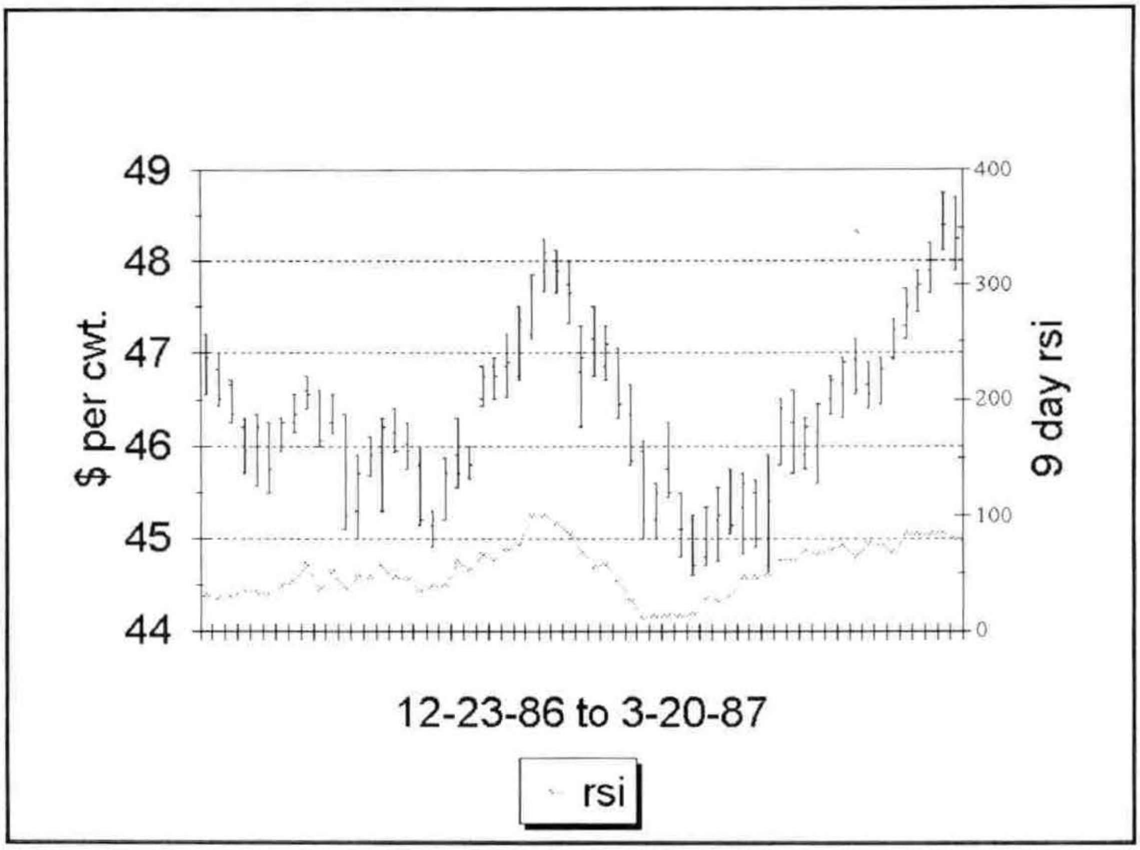

Figure 4.1 9 day RSI calculated for the June '87 live hog futures contract.

Under an assumption of oscillating price, if price has headed predominantly in one direction in the past, it is assumed to head in the other direction in the future. Thus with ORSI, high RSI values are sell signals and low RSI values are buy signals. When a day's RSI first reaches or goes above a selected critical sell level, a contract is sold on the following day's open. When the RSI first reaches or goes below a critical buy level, a contract is bought on the following open. 49 different combinations of buy and sell levels were tested across 27 different day lengths for each of 9 ORSI GTMs in this study. The critical RSI buy levels ranged in value from 0 to 30 and the sell levels ranged from 70 to 100, both in steps of 5.

In all, 11,907 individual trading rules were tested for the general technical analysis trading strategy of ORSI (1,323 day length buy-sell combinations tested over 9 different stop loss strategies). Each of these 11,907 individual rules was tested in each of the '87-'88, '89-'90 and '91-'92 time periods. That many observations would be expected to show some profitable results on a given price history, even if that price series was randomly generated. This study seeks to minimize the weight given individual trading rules that look profitable historically. Only the ex post performance of historically optimized trading rules should be considered relevant in evaluating profitability.

Results

Table 4.1 represents the out of sample period results for the 9 individual ORSI GTM trading rules selected on the basis of '87-'88 profit while Table 4.2 represents the 9 methods selected on the basis of '87-'88 index scores. Note that f stands for fixed and t stands for trailing under the stop loss rule column. (e.g., f250 represents a fixed stop of $250.00). The most profitable out of sample trading rule in table 4.1 was a 9-15-100 rule using a fixed stop of $750.00. The 9 represents the N day length used to compute the RSI, the 15 represents the RSI buy level and the 100 is the RSI sell level. This rule generated a $3920.00 profit and had a maximum drawdown of -$1100 in '89-'90. In '91-'92 it had a $3970.00 profit with a maximum drawdown of -$1220. In '89-'90, 50% of the total trades were profitable. In '91-'92, 67% of total trades were profitable. It generated 11 total trades for the 4 year out of sample period of 1989 to 1992. The least profitable out of sample performance in Table 4.1 was a 16 day RSI with a buy level of 30 and a sell level of 90 using a trailing $250 stop. It lost a total of $3880 over the 4 year period.

The most profitable out of sample trading rule selected by the index score is found in Table 4.2 and was a 9-20-100 rule using a fixed $750.00 stop. The worst performing index selected rule was a 13 day RSI using a 30 buy level, 95 sell level and a $250 trailing stop loss. The same day length buy-sell level appears as an optimized selection under more than one stop loss strategy. Also, the same rule was selected by the profit and index criteria at times, resulting in a combined total of 13 different rules. While the stop level strategy did affect results, it appeared that the fit of an individual trading rule to the '87-'88 data was more dependent on the day length and buy and sell parameters than it was on the stop loss strategy. The day length parameter was tested from 4 to 30. The optimum day length selected on the basis of both profit and the index ranged in length from 8 to 16 days. Market commentators often use an RSI of 30 as the threshold level for an oversold condition and a 70 level for an overbought condition on a 9 or 14 day RSI. While the optimum buy level selected was 30 in 12 out of 18 cases for both profit and index optimization, the sell level tended to be at the extreme high end, ranging from 90 to 100 in every case. The results suggest that perhaps an RSI buy level higher than 30 should have been tested in the study. Since the maximum possible level for an RSI is 100, the optimum selections suggest that the 70 to 100 range tested for sell levels was adequate.

The out of sample profits seem rather high (recognizing that many of the methods selected were similar). The total 4 year profit for all of the ORSI profit optimized trades was \$24,480 generated from a total of 158 trades for an average profit of \$154.94 per trade. The total 4 year profit for the index selected group was \$22,720 earned on 226 total trades for an average profit of \$100.53.

For the profit optimized group, the average 2 year total profit for the no stop loss rule was \$1030 (only 2 period observations). For the fixed stop rules the average 2 year total profit was \$2,740 and for the trailing stop rules the average profit was \$62.50.

The correlations of profit between periods for each of the 9 ORSI GTMs are presented in Table 4.3. The correlation of profit between periods is calculated on all 1323 individual trading rule profit observations per period for each GTM listed in the table. They are uniformly positive and surprisingly high. A positive correlation merely suggests that when the earlier period observed profit for a specific buy-sell level is above its mean, the other periods' observation on the same buy-sell level tends to be above its mean also, and vice versa. It should be noted that the observations in the profit vectors used in calculating the correlation statistic were not just the profit optimized results but all of the profit results, and many were negative. Indeed, all of the GTMs in all of the periods had negative mean profits. The high positive correlation values tend to support the profitable performance of the individual trading methods selected in the '87-'88 period and tested out of sample. Had the worst profitable trading methods been selected in '87-'88, the positive correlation statistics suggest that they probably would have performed poorly out of sample as well.

Table 4.1 Out of sample results of ORSI trading rules historically optimized on '87-'88 profit

stop loss rule	day l. buy l. sell l.	89-90 profit	91-92 profit	89-90 max. d.d.	91-92 max d.d.	89-90 ratio + trades	91-91 ratio + trades	89-92 total trades
none	10-30-95	-$20	$2080	- $620	-$1530	0.6	0.6	15
f250	9-15-100	$900	$3930	-$1620	-$1260	0.18	0.4	16
f500	8-10-100	$1610	$3910	-$170	-$1220	0.43	0.67	10
f750	9-15-100	$3920	$3970	-$1100	-$1220	0.5	0.67	11
f1000	10-30-95	$2060	$1620	-$720	-$1990	0.5	0.43	19
t250	16-30-90	-$3920	$40	-$4480	-$2050	0.22	0.5	30
t500	8-10-100	-$690	$2090	-$970	-$110	0.29	0.75	11
t750	10-30-95	$1590	-$1200	-$1440	-$3670	0.41	0.36	31
t1000	16-30-95	-$1060	$3650	-$2260	-$1420	0.38	0.57	15

Table 4.2 Out of sample results of ORSI trading rules historically optimized on '87-'88 index values

stop loss rule	day l. buy l. sell l.	89-90 profit	91-92 profit	89-90 max. d.d.	91-92 max d.d.	89-90 ratio + trades	91-92 ratio + trades	89-92 total trades
none	10-30-95	-$20	$2080	- $620	-$1530	0.6	0.6	15
f250	16-30-95	-$1480	$1190	-$1980	-$3110	0.2	0.22	19
f500	8-10-100	$1610	$3910	-$170	-$1220	0.43	0.67	16
f750	9-20-100	$3080	$3330	-$1100	-$1860	0.43	0.5	11
f1000	10-30-95	$2060	$1620	-$720	-$1990	0.5	0.43	19
t250	13-30-95	-$770	-$140	-$2180	-$1500	0.24	0.41	53
t500	10-30-95	$200	$2450	-$1440	-$1060	0.33	0.61	36
t750	10-30-95	$1590	-$1200	-$1440	-$3670	0.41	0.36	31
t1000	10-30-95	$1590	$1620	-$720	-$1860	0.47	0.45	26

The individual stop loss strategies listed in the first column of Table 4.3 represent the 9 different ORSI GTMs. Each of the next 3 columns represent the correlation statistic calculated between two periods and the last column represents the simple average correlation calculated from the 3 listed pairs of periods. The average of the values reported in column 5 of Table 4.3 is .61 and is reported for comparison purposes with the other 3 trading methods.

For purposes of comparing period correlation of profit between general stop strategies, column 5 was averaged by stop strategy. It was found to be .62 for the 4 fixed stop levels and .62 for the trailing stop levels in the table. The no stop loss rule had an average correlation across the periods of .56.

Table 4.3 ORSI period correlation statistics

stop loss	87-88 89-90	87-88 91-92	89-90 91-92	average
none	0.63	0.64	0.42	0.56
f250	0.74	0.73	0.55	0.68
f500	0.71	0.66	0.51	0.62
f750	0.69	0.64	0.52	0.61
f1000	0.62	0.63	0.45	0.57
t250	0.80	0.79	0.64	0.74
t500	0.83	0.58	0.45	0.62
t750	0.74	0.45	0.38	0.52
t1000	0.72	0.62	0.42	0.59

The mean profits and mean standard deviations of profit in Table 4.4 represent the mean 2 year profit and standard deviation of 2 year profit for all rules tested in the entire 1987 to 1992 period for each ORSI stop loss strategy. They reflect how well a GTM fit the entire historical data series. The large standard deviations for all of the methods and negative mean profits mean that the ORSI GTM profits are not greater than zero at the 5% significance level. All of the z scores are strongly negative and less than the 1.645 critical value so that the null hypothesis of zero profit is not rejected for any ORSI GTM. It would seem that in order to be profitable, it would be necessary to find an optimum parameter set for any of the ORSI GTMs or be lucky. The limited data set used does not totally rule out luck, but the appearance of the out of sample profits for ORSI do not argue in that direction.

Table 4.4 ORSI 1987-1992 2 year mean profit, standard deviation of profit and z scores.

stop loss	mean profit	std. dev.	z scores
none	-$1,746.68	$4,109.27	-26.78
f250	-$2,353.95	$4,371.78	-33.92
f500	-$1,754.00	$4,113.15	-26.87
f750	-$1,705.82	$4,047.10	-26.55
f1000	-$1,589.41	$3,999.98	-25.03
t250	-$2,655.77	$3,765.43	-44.43
t500	-$2,381.76	$3,752.87	-39.98
t750	-$1,938.21	$3,513.12	-34.76
t1000	-$2,000.91	$3,751.82	-33.60

The best performing GTM was the fixed stop level of 1000 that had a mean 2 year loss for the 6 year period of $1,589.41 and a standard deviation of profit of $3,999.98 which happened to be the median standard deviation of the 9 observed for ORSI. The worst performing GTM was the trailing $250 stop loss strategy which showed a mean 2 year loss of $2,655.77 for the six year period and a standard deviation of $3,765.43.

The ORSI trading strategy tested that best fit the entire 1987-1992 period for the two contracts was a 7 day RSI using a 15 buy level, 100 sell level and a $1000.00 trailing stop loss. It generated $22,700.00 in profits (all profits and drawdowns include a $90.00 transaction fee). It had its largest drawdown in the 1989-1990 period of -$1200.00 and generated 21 winning trades out of a total of 31. The worse performance of the ORSI strategies tested came from a 4 day RSI with a 15 buy level, 75 sell level and a $250.00 trailing stop. It lost -$43,420 generating 79 winning trades out of a total of 251. Its largest drawdown occurred in 1987 to 1988 , -$16,970. Neither the best or worst performing trading rules were selected by the historical optimization procedures. They are presented as a way of representing the range of performance over the entire 1987 to 1992 period and to quantify the extreme degrees of risk and reward for the period.

The overall average of profit and standard deviation of profit by stop loss strategy was calculated from Table 4.4 to compare performance of general stop loss strategies. The no stop level from row one in the table had a mean profit of -$1,746.68 with an average standard deviation of $4,109.27. The fixed stop levels had an average mean profit of -$1850.80 with a average standard deviation of $4,133. The trailing stop levels had an average mean profit of -$2244.16 with an average standard deviation of $3,695.81. The z scores for each of the stop strategies indicate that the null hypothesis of zero profits for each strategy cannot be rejected.

Conclusions

ORSI on the whole does not appear to fit the 1987-1992 live hog futures data very well. The no stop loss results in Table 4.4 probably most closely reflect the fit of the basic ORSI strategy to the data, since trading signals come only from the ORSI method and the expiration of the contract. The results also reflect the entire 6 years of data. The no stop method lost money and had a large variance. Negative mean profits and large standard deviations of profit were found for every stop strategy in Table 4.4. Results from this research suggest that the random selection of a day length and buy and sell level for ORSI would not be expected to perform well for any of the stop strategies tested, including no stop loss. The no stop loss strategy had the largest mean profit of any of the stop strategies, -$1,746.68, although it had a negative mean profit for the 6 year period. This suggests that the basic ORSI strategy was not improved by the addition of a stop loss rule. The stop level did affect results. The average of the 4 fixed stop loss summary 1987-1992 profits (from Table 4.4) was -$1850.80 while the average for the 4 trailing stops was -$2,244.16.

In contrast to the negative conclusion regarding ORSI generally, specific ORSI trading rules had surprisingly positive ex post profits when selected historically on the basis of profit and the index. Both profit and index historically optimized individual trading rules were much less profitable out of sample in the '89-'90 and '91-'92 periods than they were in '87-'88. This is not surprising since each was the best performer out of 1323 possibilities in the '87-'88 period with regard to profit and with regard to the index which was based on both period sum of profits and sum of losses. The consistency of out of sample positive profits for both groups was surprising. To some extent, this was due to the same trading rule being selected by both criteria or because the same day length and buy-sell level was optimum with different stop strategies within a selection criteria.

The out of sample profits for the rules selected on the basis of profit for the '89-'92 period totaled \$24,480 on 158 trades for an average trade profit of \$154.94. The no stop rule averaged \$1030 profit per 2 year period, the fixed stop rules averaged \$2,740 and the trailing stop rules \$62.50. For the index optimized rules the total '89-'92 profit was \$22,720 obtained from 226 trades for an average profit of \$100.53 per trade. The average 2 year profit for the no stop loss rule was \$1030 (the same rule as profit optimization was selected), while the fixed stop average was \$1915 and the trailing stop \$667.50. These results, coupled with consistently positive correlations between period profits for all specific parameter combinations, leads to a conclusion that historical optimization based on both profit and the index was effective, based on the 4 year out of sample period results. Profit optimization obtained slightly better out of sample results than those of the index selected rules.

Out of sample results suggest that a fixed stop loss rule is preferable to a trailing stop loss or no stop loss at all. This is a different conclusion than that reached by looking at the stop loss strategy over all possible rule combinations over 6 years (Table 4.4), although the fixed rule performed better than the trailing stop loss in that case.

The results of this study of ORSI suggest that the conclusion regarding the effectiveness of ORSI used on live hog futures is linked to the conclusion of whether ORSI historical optimization is effective. This study supported the conclusion that historical optimization is effective.

CHAPTER 5
TRENDING RELATIVE STRENGTH INDEX

Procedure

The TRSI research procedure was very similar to the one used for ORSI explained in the previous chapter. TRSI uses the same RSI statistic as ORSI but operates from a different philosophy with regard to future price direction. TRSI assumes that price trends continue. Since high RSI values are formed by higher trending prices and low RSI values by lower trending values, TRSI buys when RSI is relatively high and sells when RSI is relatively low. This is the opposite of the ORSI strategy. TRSI was evaluated over the same number of RSI day lengths as ORSI (4 to 30). Like ORSI, the buy and sell critical levels for the RSI were 0 to 30 and 70 to 100 in steps of 5, but this time the high values were buy signals and the low values were sell signals.

All four of the technical analysis methods used in this study, including TRSI, utilize the same 9 stop loss strategies and methods of calculating the historical index, summary correlation statistics and 1987-1992 mean and standard deviation of profit. The same general historical optimization and testing strategy is used in all 4 methods as well. The main difference in procedure between ORSI, TRSI, DMA and DMI involves the parameters used in each and their method of calculation and use. The parameters used for TRSI and their method of calculation are the same as for ORSI. The use of RSI with the TRSI method involves the reversal of roles for the buy and sell levels of RSI as used in ORSI. There were 1323 individual rules tested for each TRSI GTM or stop loss strategy and 11,907 individual rules tested overall.

Results

The same tabular format is utilized for all 4 technical analysis methods in reporting results. Tables 5.1 and 5.2 report TRSI out of sample results for individual trading rules selected as optimum for each stop loss strategy in the '87-'88 period. Note the reversal of order for the buy and sell levels. The rule identification consists of day length, sell level then buy level. (Tables 4.1 and 4.2 listed buy level then sell level). There were identical day length buy-sell combinations selected as optimum for different stop loss strategies for TRSI. The same rules were selected as optimum by both the profit and the index criteria for the fixed stop loss strategies, and only 2 rules were different for the trailing stops. There were only 11 different individual trading rules selected from a possible 18 different stop loss / optimization combinations. Overall, the out of sample profits were remarkably consistent, although based on only 11 observations. Only 2 optimized methods lost money in 4 years. The 8-0-80 no stop loss strategy made $8,460 on 11 trades in 4 years and was the best performer out of sample. The worst performing out of sample rule, the 12-20-70 $250 trailing stop method, had buy and sell levels that were not near the extremes for RSI values, and had a close trailing stop loss level. It had the largest number of out of sample trades for TRSI, a total of 54 in 4 years. It appears from Tables 5.1 and 5.2 that the more profitable trading rules tend to be ones that trade less frequently than others. The most profitable 8-0-80 no stop loss combination had the least number of out of sample trades (11).

Winning trade percentages across all selected optimized rules tended to be less than 50%. This, combined with a profitable performance on average meant that the size of the winning trades were larger than the losing trades. Day lengths selected ranged from 8 to 21. There were a number of rules selected as optimum with a buy level of 70 suggesting that the range of 70 to 100 for the buy level could have been wider.

Total 4 year profit for the TRSI profit optimized trades was $27,000 generated from 201 trades for an average profit of $134.32 per trade. The total 4 year profit for the index selected group was $29,780 earned on 186 trades for an average profit of $160.11.

For the profit optimized group, the average 2 year total profit for the no stop loss rule was $4230. For the fixed stop rules average 2 year total profit was $1725 compared to $940 for the trailing stops.

Table 5.1 Out of sample results of TRSI trading rules historically optimized on '87-'88 profit

stop loss rule	day l. sell l. buy l.	89-90 profit	91-92 profit	89-90 max. d.d.	91-92 max d.d.	89-90 ratio + trades	91-91 ratio + trades	89-92 total trades
none	8-0-80	$4040	$4420	-$3040	-$470	0.33	0.60	11
f250	8-0-80	$4780	-$3160	-$1330	-$3160	0.30	0.14	24
f500	21-10-70	$1490	$620	-$3850	-$680	0.25	0.43	15
f750	21-10-70	$2070	$1370	-$3240	-$1120	0.43	0.50	13
f1000	7-0-75	$4700	$1930	-$2150	-$1610	0.50	0.38	16
t250	12-20-70	-$730	-$4550	-$1790	-$4590	0.38	0.28	54
t500	12-5-70	$270	-$760	-$2820	-$1220	0.33	0.43	29
t750	12-5-70	$5990	-$2210	-$2550	-$2320	0.56	0.31	22
t1000	12-5-70	$6150	$580	-$2880	-$2020	0.50	0.44	17

Correlation values for TRSI are found in table 5.3. Only one period to period correlation of profit had a negative value for TRSI. The values were consistently positive, although not as positive in magnitude as ORSI. The overall average correlation was .35. The overall average correlation for the fixed stop strategies was .37, and .31 for the trailing stops. Both the fixed and trailing stop correlation of profits were less than .49 for the no stop strategy. The positive correlations of profits between periods for all rules support the results of historical optimization of TRSI, which found positive profits in the '87-'88 period continuing through the subsequent periods.

Table 5.2 Out of sample results of TRSI trading rules historically optimized on '87-'88 index value

stop loss rule	day l. sell l. buy l.	89-90 profit	91-92 profit	89-90 max. d.d.	91-92 max d.d.	89-90 ratio + trades	91-91 ratio + trades	89-92 total trades
none	8-0-80	$4040	$4420	-$3040	-$470	0.33	0.60	11
f250	8-0-80	$4780	-$3160	-$1330	-$3160	0.30	0.14	24
f500	21-10-70	$1490	$620	-$3850	-$680	0.25	0.43	15
f750	21-10-70	$2070	$1370	-$3240	-$1120	0.43	0.50	13
f1000	7-0-75	$4700	$1930	-$2150	-$1610	0.50	0.38	16
t250	7-0-75	-$50	-$3210	-$930	-$3880	0.48	0.33	45
t500	12-5-70	$270	-$760	-$2820	-$1220	0.33	0.43	29
t750	12-5-70	$5990	-$2210	-$2550	-$2320	0.56	0.31	22
t1000	11-5-70	$4040	$3450	-$2920	-$310	0.33	0.60	11

1987 to 1992 period mean 2 year profits were generally positive for TRSI with only 2 out of 9 stop loss strategies showing negative profits. This is not surprising after looking at ORSI and realizing TRSI was tested on the same data set and basically takes positions in the opposite direction. (The previous chapter noted negative mean profits for ORSI). The standard deviations of profit are quite large for TRSI. There was considerable variance in profit levels between day length buy-sell levels as well as between 2 year periods for individual trading methods, and both of these sources of variation are reflected in the high standard deviations of 1987-1992 profit for each GTM. The alternative hypothesis of positive mean profits is accepted for all of the stop levels except the trailing $250 and $500 stops at the 5%

significance level. For those stops the null hypothesis (that their mean profits are zero) is not rejected at the 5% significance level.

The best performing TRSI GTM was the fixed $250 stop loss strategy with a 2 year average profit of $815.23. The worst performing GTM was the trailing $500 stop loss with a -$685.60 2 year average profit.

Table 5.3 TRSI period correlation statistics

stop loss	87-88 89-90	87-88 91-92	89-90 91-92	average
none	0.55	0.55	0.36	0.49
f250	0.46	0.23	0.65	0.45
f500	0.45	0.34	0.13	0.31
f750	0.52	0.46	0.30	0.43
f1000	0.53	0.57	0.31	0.47
t250	0.23	-0.15	0.20	0.10
t500	0.22	0.22	0.39	0.28
t750	0.68	0.10	0.28	0.35
t1000	0.62	0.48	0.37	0.49

The TRSI individual trading rule with the best profit for the 1987- 1992 period overall was an 11 day RSI with a buy level of 70 and a sell level of 0 with no stop loss. It had a total profit of $20,430 on 12 trades and had a maximum 2 year period drawdown of -$2,380. The worst performing individual trading rule was a 14 day RSI with a buy level of 95 and a sell level of 30. it lost -\$24,060 on 13 trades and had a maximum 2 year period drawdown of -\$13,120.

The average 2 year profit and standard deviation of profit by stop loss category, calculated from Table 5.4 were: \$595.89 and \$4,075.97 for the no stop loss, \$627.84 and \$3,190.31 for the fixed stop and -\$113.29 and \$2,484.98 for the trailing stop.

Table 5.4 TRSI 1987-1992 2 year mean profit, standard deviation of profit and z scores.

stop loss strategy	mean profit	standard deviation	z scores
none	\$595.89	\$4,075.97	9.21
f250	\$815.23	\$2,968.64	17.30
f500	\$608.83	\$3,067.98	12.50
f750	\$509.32	\$3,299.30	9.73
f1000	\$577.97	\$3,425.32	10.63
t250	-\$612.39	\$1,901.24	-20.29
t500	-\$685.60	\$2,041.25	-21.16
t750	\$230.28	\$2,917.89	4.97
t1000	\$614.57	\$3,079.54	12.57

Conclusions

Using the no stop method results for the entire 6 year period from Table 5.4 as a proxy for the fit of the general TRSI method to the data, TRSI appeared to fit the data somewhat better than ORSI, although the standard deviation is quite large. In this case, a stop loss strategy appears to improve the general TRSI method. The fixed stop loss outperformed the trailing stop loss and no stop loss strategy in Table 5.4. The out of sample results in Tables 5.1 and 5.2 favored the no stop loss strategy, but the fixed stop was superior to the trailing stop there also.

The out of sample profits of the historically optimized TRSI methods were overall quite positive. The generally positive mean 1987-1992 profits tend to detract from the strength of conclusions regarding the effectiveness of historical optimization applied to TRSI. Positive mean profits for most GTMs over the entire 6 year period imply that positive out of sample profits are more likely to be observed due to random chance, while large standard deviations argue that any observation is more likely due to chance, and takes away from any out of sample conclusion. Based on out of sample performance, the conclusion is drawn that historical optimization of trading parameters for TRSI based on profit and the index are both effective. The only difference between the rules selected by either criteria involved the $250 trailing stop and the $1000 trailing stop. The index appeared to be the better optimization criteria in this case since the average 2 year out of sample period profits for trailing stops was $940 versus $592.50 for those selected by profit. The confidence in that conclusion is mitigated by the fact that the difference between the optimization criteria is solely accounted for by the performance of 2 rules for each criteria.

TRSI was generally profitable out of sample in spite of generally having more losing trades than winning trades. Generally lower numbers of trades were associated with higher profits.

CHAPTER 6
DUAL MOVING AVERAGE

Procedure

A dual moving average is based on the assumption that prices trend. These trends are detected by calculating a short moving average (N_s) of daily closing prices and a longer length moving average (N_l) of closing prices. The shorter length average is more responsive to changes in price than the longer average containing more price observations. When prices do begin to trend in a different direction than the immediate past, the shorter moving average will "cross" the longer average in the direction of the emerging trend, either up or down. (When the averages are charted graphically the lines connecting each day's short and long moving averages will literally cross as in Figure 6.1). This is taken as a signal that a trend has begun. The trend is then assumed to continue until the shorter moving average crosses the longer average in the opposite direction.

Short moving average day lengths (N_s) were calculated for day lengths of from 1 to 19 in intervals of 2. Long moving average day lengths (N_l) were calculated for day lengths from 21 to 51 in intervals of 2. (51 days was selected as an upper limit for the long average because some market commentators have suggested that 40 and 50 day averages are used by some large commodity funds as a technical trading indicator).This resulted in 160 different short and long day length combinations tested. They move in the sense that an N day moving average contains today's closing price and the previous N-1 days' closing prices. A three day moving average would be calculated as follows: *(today's close + yesterday's close + the day before yesterday's close)/3*. The average "moves" in that tomorrow's 3 day moving average won't include today's oldest closing price, but will include tomorrow's close.

The basic moving average concept has been modified in two ways for this study in an attempt to model how the simple moving average method may be used in actual practice. The first modification involved the use of the same 9 fixed and trailing stops utilized on all forecasting methods. The calculation of the stop levels was the same as the other methods, and followed the same convention that once an open trade had been closed out due to a stop loss signal, a new trading signal from the indicator was required to generate a new trade. (In the case of the dual moving average, a new trading signal consisted of a crossing of the long average by the short average). The second modification involved the use of trading bands around the long moving average. Five band widths of 0, .25, .50, .75 and 1.00 dollars per cwt. were used. These band widths acted like a neutral zone around the long moving average. The short moving average was not considered to have crossed the long average unless it exceeded the band width on the other side of the long average. When the band width was 0, all that was required was a short moving average price greater than or less than the long moving average price. When the band width was greater than zero, all short average penetrations of the long average not exceeding the band were ignored. Using a $1.00 band for example, if the short average had previously been below the long average, a close of greater than $1.00 in excess of the long average price would be required to give a buy signal. Assuming that occurred, the long position would be maintained until a sell signal occurred, a stop loss was exceeded or the contract expired. A sell signal would require the short average to be $1.00 or more below the long average. The band widths were always symmetrical in their application. If a band width was used, it applied to the band width above and below the long average. All combinations of day lengths were tried using each of the 5 band widths for each of the DMA - stop loss combinations or GTMs. This resulted in a total of 800 individual trading rules for each GTM (10x16x5), or 7200 individual trading rules for the DMA method.

Like all the technical methods investigated, calculations of technical parameters (in this case long and short moving averages and the band width modification) were assumed to take place after the close of trading for the day and included the current day's price. Signals were always calculated on closing prices and executed at the following day's opening price.

Results

Tables 6.1 and 6.2 follow the same tabular format as the previous chapters. The technical parameters that distinguish an individual trading rule are the short average day length, long average day length and the band width denoted in the second column of the table. The best performing out of sample rule for DMA was a 13 day short average, 31 day long average, 1.00 band width using a fixed $1000 stop loss. It gained $4810 in the '89-'92 period and had a maximum drawdown of $1170 in '89-'90. The worst performing out of sample rule was the 3 day short average, 25 day long average with 0 band width and a trailing $250 stop. It lost $6700 in the 4 year out of sample period with a maximum drawdown in '91-'92 of $5600. The optimized performance out of sample was rather poor overall. Thirteen different distinct individual rules were chosen out of a possible 18 between the two optimization criteria. Of the 13, only 5 were profitable over the 4 year out of sample period taken as a whole.

The profit optimized rules lost $11,670 in total in the 4 year out of sample period on 263 trades for an average loss per trade of $44.37. The index optimized trades did even worse losing $16,370 on 327 trades for an average loss per trade of $50.06. The profit optimized rules did better as a whole than the index selected rules.

The day lengths selected as optimum were widely dispersed throughout the range studied as were the band widths. The best performing out of sample method happened to fall towards the middle of the range of day lengths with a 13 day short length and a 31 day long length.

Period correlation values were very close to zero for DMA generally. The overall average correlation value was .10. Either correlation values were close to zero for a particular DMA stop loss rule or there was little consistency in correlation values between periods. There were quite a few negative correlation statistic values overall and often they were interspersed with positive correlations in other periods. The average of the fixed stop loss correlations in column 5 of table 6.3 was .09 while those of the trailing correlations was .12. Since the no stop loss rule had an average correlation of .10 there was virtually no difference in correlation values between the 3 different stop loss strategies.

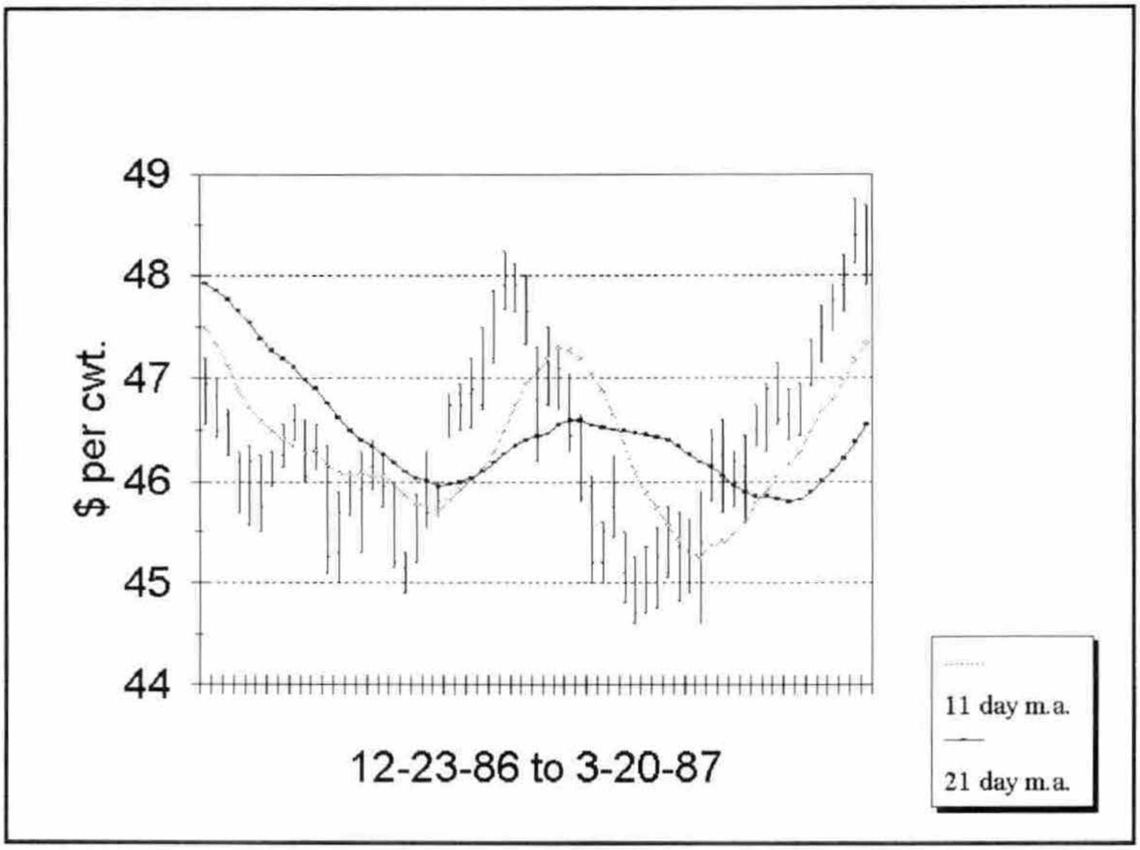

Figure 6.1 11 day and 21 day moving averages calculated for the June '87 live hog futures contract.

Only 2 of 9 GTMs had negative mean profits for the 1987-1992 period. There was a great deal of variation in profits as the standard deviation values in Table 6.4 indicate. The stop loss strategy that best fit the entire 6 years of data was the fixed $1000 stop loss, with a 2 year mean profit of $1,004.85. The worst fitting stop loss strategy was the trailing $500 stop loss which had a mean 2 year loss of $2,087.29. The average 2 year profit for the fixed stop methods in table 6.4 was $886.65 with an average standard deviation for the fixed group of $3,046.45. The average mean profit for the trailing stop methods in the table was -$449.55

with a standard deviation of $2,431.54. Based on the calculated z scores in Table 6.4, the alternative hypothesis that mean profits are greater than zero at the 5% significance level is accepted for all but the trailing $250 and $500 stops, where the null hypothesis that their mean profits are zero cannot be rejected.

Table 6.1 Out of sample results of DMA trading rules historically optimized on '87-'88 profit

stop loss rule	s. days l. days band	89-90 profit	91-92 profit	89-90 max. d.d.	91-92 max d.d.	89-90 ratio + trades	91-91 ratio + trades	89-92 total trades
none	13-31-1.00	$2960	$1370	-$1170	-$230	0.43	0.50	9
f250	3-51-1.00	$2430	$250	-$1440	-$460	0.43	0.50	13
f500	7-47-1.00	-$1630	-$790	-$3760	-$1500	0.22	0.50	15
f750	7-47-1.00	-$2070	-$1300	-$3520	-$2010	0.33	0.50	15
f1000	13-31-1.00	$3440	$1370	-$1170	-$230	0.43	0.50	9
t250	7-27-0.00	$640	-$5120	-$1390	-$5290	0.43	0.21	52
t500	19-39-1.00	-$3050	-$910	-$3050	-$910	0.00	0.00	8
t750	3-25-0.00	-$20	-$6550	-$3440	-$6740	0.34	0.26	71
t1000	3-25-0.00	$4120	-$6810	-$3440	-$7000	0.41	0.26	71

The DMA individual trading rule that best fit the 1987- 1992 data overall was a 11 day short moving average, 27 day long moving average with a $1.00 band and no stop loss. It showed a $17,270 profit over the entire 6 year period on 16 trades and had a worse case 2 year drawdown of -$1610 in '89-'90. The poorest performing individual trading rule for the entire 1987-1992 period was a 1 day short moving average, 33 day long moving average with no band and a $500 trailing stop. It lost -$23,780 on.152 trades and had a worse case 2 year drawdown of -$10,970 in '89-'90.

Table 6.2 Out of sample results of DMA trading rules historically optimized on '87-'88 index value

stop loss rule	s. days l. days band	89-90 profit	91-92 profit	89-90 max. d.d.	91-92 max d.d.	89-90 ratio + trades	91-91 ratio + trades	89-92 total trades
none	19-33-0.75	-$1190	$1570	-$1610	-$160	0.29	0.50	9
f250	5-51-0.25	$5620	-$1390	-$1550	-$2990	0.36	0.22	23
f500	7-47-1.00	-$1630	-$790	-$3760	-$1500	0.22	0.50	15
f750	7-47-1.00	-$2070	-$1300	-$3520	-$2010	0.33	0.50	15
f1000	13-31-1.00	$3440	$1370	-$1170	-$230	0.43	0.50	9
t250	3-25-0.00	-$1130	-$5600	-$2960	-$5790	0.44	0.26	71
t500	3-47-0.00	-$4530	$520	-$5800	-$810	0.26	0.45	43
t750	3-25-0.00	-$20	-$6550	-$3440	-$6740	0.34	0.26	71
t1000	3-25-0.00	$4120	-$6810	-$3440	-$7000	0.41	0.26	71

Table 6.3 DMA period correlation statistics

stop loss	87-88 89-90	87-88 91-92	89-90 91-92	average
none	0.04	0.36	-0.10	0.10
f250	0.40	-0.06	-0.28	0.02
f500	0.04	0.24	-0.06	0.08
f750	0.07	0.38	0.00	0.15
f1000	-0.03	0.34	-0.02	0.10
t250	0.55	-0.10	-0.03	0.14
t500	0.40	0.12	-0.20	0.10
t750	0.06	0.14	0.16	0.12
t1000	0.02	0.28	0.05	0.12

Conclusions

Using the no stop loss 2 year mean profit and standard deviation (from Table 6.4) as an indicator of the fit of the general DMA strategy to the data, DMA fits the data better than ORSI or TRSI. The mean 2 year profit is higher than the other methods and the standard deviation, while still quite high at $3,235.50, is the lowest of the three. It is surprising that the out of sample testing of individual rules optimized on profit and the index fared so poorly for this method, although the no stop loss optimized rules were profitable for both. It reflects poorly on the performance of DMA historical optimization both using profit and the calculated index, that out of sample profits of optimized methods were not better given the mostly positive mean profits for the entire period for most of the stop loss strategies. Neither profit or index optimization was effective across all stop strategies, but several individual stop loss strategies were profitable out of sample. The poor correlations of profit statistics are consistent with the relatively poor out of sample performance of the optimized methods.

An interesting observation on the out of sample performance of DMA centers on the rule selected by profit for the trailing $500 stop. While it was not the largest total dollar loser, losing $3,960 over 4 years, it lost money on all 8 of its trades. This runs contrary to general observations that the more profitable trading rules tend to be the ones trading fewer contracts. This rule had the fewest trades of all of the DMA optimized methods. For the other optimized DMA rules, the conclusion that fewer trades generally lead to higher profits seemed to hold.

Table 6.4 DMA 1987-1992 2 year mean profit, standard deviation of profit and z scores.

stop loss strategy	sample mean profit	sample std dev	z scores
none	$971.15	$3,235.50	14.70
f250	$882.17	$3,026.10	14.28
f500	$907.36	$2,921.94	15.21
f750	$752.23	$3,133.58	11.76
f1000	$1,004.85	$3,104.19	15.86
t250	-$916.52	$1,729.89	-25.96
t500	-$2,087.29	$2,047.48	-49.94
t750	$364.14	$3,024.23	5.90
t1000	$841.47	$2,924.54	14.10

According to Table 6.4, the addition of stop loss rules did not seem to make DMA any more profitable over the 1987-1992 period. The average 2 year profit for the 4 fixed stop loss rules was not better than the no stop strategy but was better than the trailing stop methods.

Out of sample results in Tables 6.1 and 6.2 suggest different conclusions regarding stop loss strategy. The optimization by profit results (Table 6.1) agrees with Table 6.4 that the no stop strategy is best. Optimization by index results (Table 6.2) suggest that the fixed stop strategy on average is superior. The no stop loss strategy appears to be the best stop level choice overall.

CHAPTER 7
DIRECTIONAL MOVEMENT INDEX

Procedure

DMI operates on the assumption that prices trend. It is a trend following system like TRSI and DMA but the parameters used and their method of calculation and interpretation are different. J. Welles Wilder Jr. developed the Directional Movement Index system and presented it in New Concepts in Technical Trading Systems (1978). The procedure used for DMI in this study followed a modified procedure used by Drinka and Kille (1985 pp. 40-41), but modified their procedure. DMI is by far the most complicated technical trading system looked at in this study. It requires a significant amount of lead time that exceeds its day length parameter due to its method of calculation. The calculation procedure results in 3 significant variables that together determine trading signals. The first, ADX, is considered a measure of the strength of the trend in prices either up or down. The stronger the past trend, the higher the resulting ADX calculation. Trades are initiated only when the ADX variable exceeds a minimum threshold level. The other two variables, which this study will name Dplus and Dminus are the variables that determine the direction of the trade and its timing, given that the ADX is above its threshold level. If the Dplus variable exceeds the Dminus variable a long position is established. If the Dminus exceeds the Dplus variable in value a short trade is established. No band widths similar to those used in the DMA study were used for Dplus or Dminus. Following the same convention used throughout this research, if no current position was held only one contract was traded on the following open when a crossing trading signal was generated. If an open position was held, two contracts were traded on the following open, one to close the existing position and one to establish a new position in the opposite direction.

The ADX in this study served not only as a validation requirement for issuing a trading signal based on Dplus crossing Dminus or vice versa, it also was used to generate an additional trading signal to close out a trade. This closing out of a trade on a basis other than accrued loss, was unique in this study to DMI. It also was a departure from the Drinka and Kille study (1985). The additional signal was implemented by closing out a trade on the following open anytime that the ADX parameter fell below the level required to generate a new trade. A new trading signal would then be required to get back into the market. The implementation of this additional signal meant that the DMI system was only in the market as long as the previous day's ADX level was above a minimum level.

DMI is calculated for a specific N day length. This study used day lengths from 4 to 38 in steps of 2. In order to explain the calculation of ADX, Dplus and Dminus it is necessary to first understand the calculation of several preliminary variables. HighDiff will be defined as the difference between the high price of the day and the previous day's high price. LowDiff is defined to be the difference between the day's low price and the previous day's low price. Trange is defined as the largest absolute value of the following three differences between: (1) the high and low price of the current day (2) the high price of the current day and the previous day's closing price (3) the low price of the current day and the previous day's closing price. TrSum is the sum of the previous N-1 day's Trange values plus today's Trange.

HighSum and LowSum are calculated from the previous N-1 days and today's HighDiff and LowDiff values. For each of the previous N days (including today), either HighDiff, LowDiff or neither, is determined to be relevant and is added to its respective sum variable, but never both on the same day. If the day's high is higher than the previous day's high and its low is higher than the previous day's low then HighDiff is added to HighSum and LowSum is ignored. If the day's low is lower than the previous day's low and the high is lower than the previous days high then LowDiff is added to LowSum and HighSum is ignored. If the day's high is higher and the low is lower than the previous day's values, the price difference that is greatest is added to its sum variable and the other sum variable is ignored. In the event that neither the current high nor the current low is higher or lower respectively than its previous day's counterpart, the day is ignored and no summation is done.

Dplus is calculated by taking the HighSum variable calculated for a particular day and dividing it by TrSum for that day. Dminus is likewise computed by taking the absolute value of the LowSum value for the day and dividing it by the same TrSum value for the day. The Dplus variable can be thought of as a rough measure of the amount of up movement in price relative to total movement in price over a previous N day period, while Dminus can be thought of as reflecting the ratio of down price movement to total movement over the previous N days.

ADX was calculated in the following way. A variable defined as DX was computed by the following formula: *abs[(Dplus -Dminus) / (Dplus + Dminus)] = DX*. There were no Dplus or Dminus variables available until there had been N+1 days worth of observations for each contract. The DX variable was calculated for the N+1 day onward for each individual contract. Another variable defined as DXSum was calculated as the sum of the previous N day's DX variables (including today's). The first day that a DXSum could be calculated was on the 2N + 1 day of observations. On this day the first ADX could be calculated by dividing DXSum by N and multiplying by 100. It can be seen by the method of calculating DX that when the values of Dplus and Dminus are about equal that DX is close to 0. When either Dplus or Dminus is near zero and the other is close to one then DX is close to one in value. Since DX is summed over N days and divided by N and multiplied by 100 to calculate ADX, ADX ranges in value from 0 to 100. The sharper the trend in prices either up or down, the higher the resulting ADX value. By requiring a minimum ADX value, the DMI system implicitly assumes that the strength of the past trend is an indication of its probability of continuation into the future.

16 ADX values were evaluated in this study, ranging from 5 to 80 in value in steps of 5. The same 9 stop loss rules were used for DMI as for the other three technical methods. This use of stop losses was also a departure from the Drinka and Kille (1985) study. There were 288 different individual trading rules (18 day lengths x 16 ADX levels) evaluated on each one of these stop loss rules for a total of 2592 different individual trading rules evaluated for DMI overall. Figure 7.1 is calculated on the same price series as Figures 4.1 and 6.1 and demonstrates how ADX, Dplus and Dminus respond to price changes.

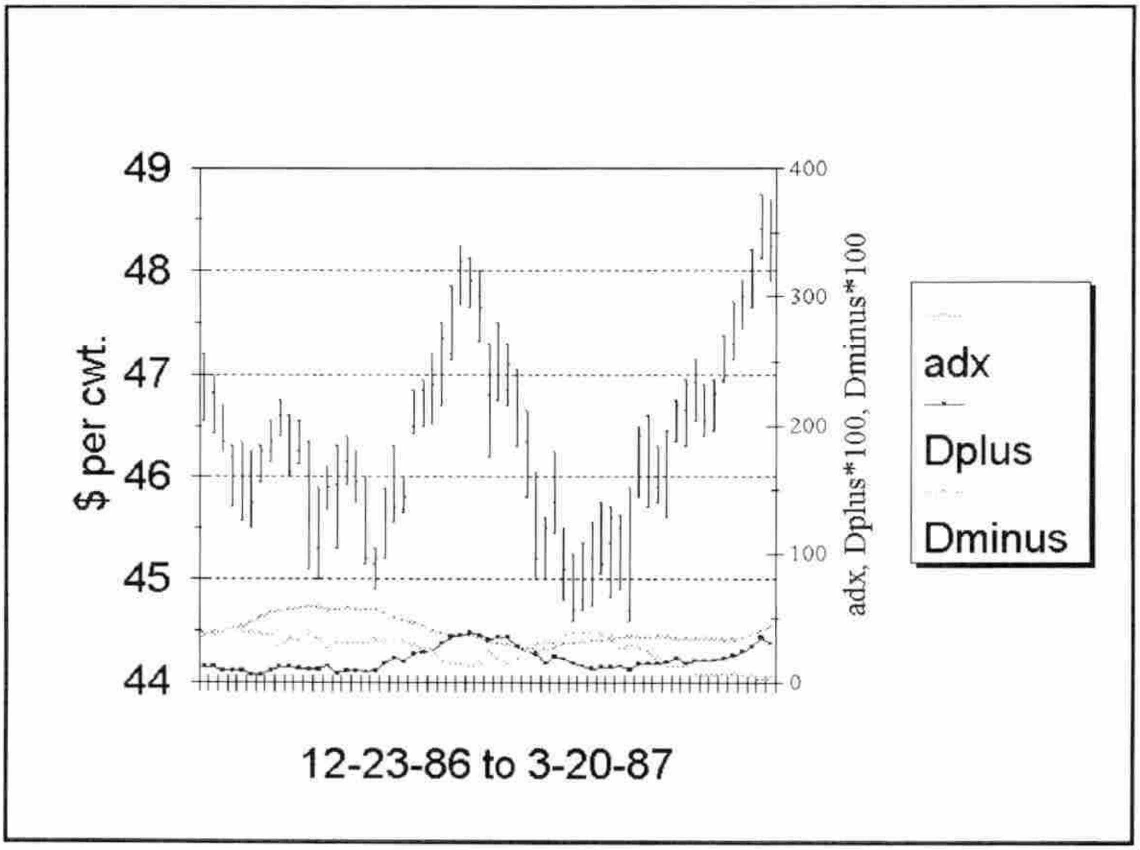

Figure 7.1 14 day DMI calculated for the June '87 live hog futures contract.

Results

There was little variation between methods selected for out of sample testing. For DMI, all of the rules selected as optimum by the historical profit criteria were also selected by the calculated index criteria. There were only 4 different day length / ADX combinations selected with the rest of the difference in rules coming from the differences in stop loss strategies. Overall, that meant that there were only 9 out of a possible 18 different individualized trading rules selected to be evaluated out of sample for this method, and total out of sample results for profit optimization exactly equaled those for index optimization.

The format for Table 7.1 is similar to the format used in previous chapters for out of sample results but represents both profit and index optimized rules since they were identical. The characteristics that distinguish an individual trading rule for DMI are the day length used in the computations and the minimum ADX value required. These characteristics of the rules selected as optimum are listed in column 2 of the tables. The best performing out of sample rule was the 34 day DMI using a 5 ADX critical level and a trailing $750 stop loss. It was the only individual trading rule having a positive profit over the 4 year out of sample period. It generated a total 4 year profit of $290 on 44 trades for the period. The worst performing optimized rule was the 8 day DMI using an ADX of 20. It lost a whopping $18,380 in the 4 year out of sample period. Overall, the out of sample results for DMI methods were very poor, even worse than DMA.

The optimized trading rules lost a total of $73,370 in 4 years of out of sample testing on 558 trades for an average -$131.49 per trade. The only profitable rule out of sample had the lowest number of trades at 44 and the worst performing rule had the largest number of trades at 111.

The correlation statistics in table 7.2 for DMI are near zero on average and are frequently negative and change signs. The average of all of the correlations in column 5 is .13 while the average for the fixed stop strategies is .09 and the trailing strategies .18. The instability of the correlations between periods can be illustrated by noting that all of the period 1 to period 2 correlations (column 2) are near zero. The correlations between period 1 and 3 (column 3) are strongly negative and period 2 to period 3 correlations (column 4) are strongly positive.

The best stop loss strategy for DMI for the entire 6 year study period was the fixed $250 stop loss. It had a mean 2 year profit of -$1,205.16 and a standard deviation of $3,282.94. The worst stop strategy had a mean profit of -$1,484.65 and standard deviation of $3,109.09 and was the trailing $500 stop loss method. The average mean profit and standard deviation of profit for the 6 year period for fixed stops was -$1,278.59 and $3,361.76.

Corresponding values for the 4 trailing stops was -$1,340.21 and $3,191.43 respectively. Overall performance of the DMI system in this study was extremely poor. Z scores were strongly negative for all stop loss strategies so that the null hypothesis of zero profit was not rejected for any stop loss strategy at the 5% significance level.

Table 7.1 Out of sample results of DMI trading rules historically optimized on '87-'88 profit and index

stop loss rule	day l. adx	89-90 profit	91-92 profit	89-90 max. d.d.	91-92 max d.d.	89-90 ratio + trades	91-91 ratio + trades	89-92 total trades
none	18-20	-$3020	-$7120	-$4200	-$7800	0.25	0.24	61
f250	16-20	-$2390	-$3740	-$3080	-$4420	0.28	0.33	55
f500	16-20	-$710	-$5580	-$2990	-$6260	0.32	0.33	55
f750	16-20	-$710	-$6230	-$2990	-$6910	0.32	0.33	55
f1000	18-20	-$3020	-$7120	-$4200	-$7800	0.25	0.24	61
t250	16-20	-$1760	-$3970	-$2520	-$4650	0.32	0.30	55
t500	8-20	-$5790	-$12590	-$5880	-$12590	0.32	0.25	111
t750	34-5	$6010	-$5710	-$3040	-$6810	0.47	0.22	44
t1000	18-20	-$3020	-$6900	-$4200	-$7580	0.25	0.24	61

Table 7.2 DMI period correlation statistics

stop loss	87-88 89-90	87-88 91-92	89-90 91-92	average
none	-0.01	-0.33	0.61	0.09
f250	0.06	-0.29	0.62	0.13
f500	-0.09	-0.37	0.63	0.06
f750	-0.02	-0.33	0.63	0.09
f1000	-0.01	-0.33	0.61	0.09
t250	0.16	-0.07	0.76	0.28
t500	0.12	-0.05	0.73	0.27
t750	-0.08	-0.36	0.70	0.09
t1000	-0.03	-0.32	0.61	0.09

The DMI trading strategy tested that best fit the entire 1987-1992 period for the two contracts was a 34 day length DMI using an ADX level of 5 and a $1000.00 trailing stop loss. It generated $9,920 in profits over the six year period. It had its largest drawdown in the 1991-1992 period of -$6390 and generated 32 winning trades out of a total of 79. The worse performance of the DMI strategies tested came from a 6 day DMI with a 20 ADX level and a $750.00 trailing stop. It lost -$30,850 generating 59 winning trades out of a total of 227. Its largest drawdown occurred in 1991 to 1992 , -$17,270.

Conclusions

The DMI method as defined and used in this study did not fit the data well. The 6 year summary mean 2 year profits found in table 7.3 are consistently negative with wide standard deviations. Only ORSI looked worse over the 6 year period (Table 4.4). The fixed stop loss strategy average 2 year mean profit and standard deviation looked slightly better than a no stop loss strategy over the 6 year period. Profits were so poor in the out of sample study of individual rules that DMI as used in this study does not appear worthy of consideration as a trading tool. Historical optimization using profit or the index does not appear to be viable. Unstable correlation statistics supported the poor observed out of sample profits of the optimization methods.

The results for DMI tend to support the concept that the most profitable trading rule tends to generate fewer trades. The DMI method had the largest number of out of sample trades of any of the 4 technical methods and turned in the worst performance out of sample. Within the DMI method itself, the only out of sample rule to have a positive 4 year profit had the lowest number of trades (44) which was still high in comparison to the other studies. The worst performing DMI out of sample rule had the largest number of trades of any rule for the entire study at 111.

It was unfortunate that DMI did not have more diversity in the rules selected as optimum in the out of sample study. This redundancy in rules allowed the few rules picked to have a large weight on the overall results and limited the number of out of sample observations of performance.

It is appropriate to note that the decision to use ADX to both enter as well as exit trades was done at the beginning of the study on the rationale that if ADX measures the strength of a trend and ADX is useful as a gauge of when to enter a trade, it should be useful to measure when the trend is waning and it is time to exit. The decision to use the same ADX level as an entry and exit signal was an arbitrary one that limited the number of trading rules that were quite large to begin with. In light of the poor performance by the method, it would be interesting to explore whether performance would improve if the ADX exit level was allowed to differ from the ADX entry level in a future study. It could be allowed to vary independently and also to not be used at all as an exit signal. This type of a study would increase the number of trading rules looked at by a significant amount.

Table 7.3 DMI 1987-1992 2 year mean profit, standard deviation of profit and z scores.

stop loss strategy	sample mean profit	sample std dev	z scores
none	-$1,300.97	$3,390.37	-18.80
f250	-$1,205.16	$3,282.94	-17.98
f500	-$1,277.79	$3,385.14	-18.49
f750	-$1,316.28	$3,386.68	-19.04
f1000	-$1,315.13	$3,392.28	-18.99
t250	-$1,340.05	$2,963.50	-22.15
t500	-$1,484.65	$3,109.09	-23.39
t750	-$1,267.62	$3,339.45	-18.60
t1000	-$1,268.51	$3,353.67	-18.53

CHAPTER 8
SUMMARY AND CONCLUSIONS

This study investigated whether 4 methods of technical analysis applied to the live hog futures market were profitable. An Oscillating Relative Strength Index, Trending Relative Strength Index, Dual Moving Average and Directional Movement Index were tested over various parameter combinations and stop loss strategies using 1987-1992 live hog futures prices.

One of the handicaps in trying to determine whether technical analysis works in forecasting futures prices is the huge number of possible combinations of parameters and stop loss rules that can be devised to trade futures markets with technical analysis. In the interest of keeping the study tractable, this research was limited to researching 4 technical analysis methods, of which 3 depended on trending prices and one depended on oscillating prices. 9 stop loss strategies were implemented for those methods that both reflected different degrees of loss aversion in traders and how the trading methods might be used in actual practice. Ranges of parameter values for each method were selected in an attempt to reflect common usage while limiting the ultimate number of trading rule variations to a workable number.

Another handicap in concluding whether technical analysis is effective concerns the data set used to draw the conclusion. The ultimate test of effectiveness is the actual real world ex ante' use of technical analysis in the futures markets. This study used the actual price history of the December and June live hog futures contracts from 1987 to 1992. Only December and June were used to keep the study tractable. The data had the advantage of being known to be the result of the actual real world price generating process and was tradeable. The data had the disadvantage of being noncontinuous and unable to take advantage of large sample statistical properties which could be obtained by an artificial price series. Conclusions regarding historical profits were subject to estimation errors regarding transaction costs, including slippage. (Transaction costs are verifiable by actually trading the market, but that type of research was beyond the financial means of this study).

Conclusions regarding the profitability of technical analysis used in futures markets utilizing both actual historical price series and studies utilizing artificially generated price series depend on the premise that the study series represents future actual price series. This is ultimately testable by using an actual future price series ex ante', but the time required for that type of study was beyond that available for this research. This study's use of all the individual trading rule results in the summary 6 year profits and the use of only out of sample results for specific optimized trading rules, attempted to deflect criticism that results were obtained from "curve fitting" historical data.

This study relies on the out of sample results of trading rules historically optimized in '87-'88 on the basis of profit and a profit-loss index to draw conclusions regarding the effectiveness of technical analysis in the live hog futures market. ORSI and TRSI were the best performing technical analysis methods studied and were profitable across various stop loss strategies for the 4 year out of sample period of 1989-1992. DMA performed better out of sample than DMI but both had negative average returns. DMA was profitable out of sample for the fixed and no stop loss strategies but performed poorly with a trailing loss. DMI performed poorly for all stop loss combinations. Technical analysis was found to be profitable in the live hog futures market on the basis of the profitable out of sample performance of ORSI and TRSI.

That optimized ORSI and TRSI both should both be profitable is at first glance a paradox, since they depend on the same trend statistic, RSI, but have opposite assumptions regarding future trends in price. If the optimized buy and sell levels of RSI tend to identify the beginning of trends for the TRSI method and the end of trends for ORSI, there is no reason that they could not both be profitable unless their buy levels equaled the other methods' sell level and they were both using the same day length for calculating the underlying RSI statistic.

One of the more interesting results of this study was the finding that the correlation of profits across periods seemed to correspond closely with the out of sample results using historical optimization. In spite of a poor overall profit performance on the 1987-1992 data, ORSI had strong positive correlations of period profits and good out of sample profit performance with individual optimized rules. TRSI had positive overall profits on the 1987 - 1992 data, strong positive correlation values, and performed well out of sample. DMA had a good overall 6 year profit but low correlation statistics and optimized trading rules did not perform well out of sample. DMI had a poor overall profit and low correlation values and optimized trading rules performed poorly out of sample.

It would be interesting to evaluate in a future study, whether the correlation of profits between periods had the same correspondence to subsequent historical optimization results when looking at other technical trading methods, or these same methods using different futures or securities market data.

Other suggestions for future research include looking at DMA with no symmetry in band width above and below the long moving average required, looking at DMI without the symmetry constraint on the ADX entry and exit signals, and the incorporation of correlation of profits across periods as a way of screening potential candidates for technical analysis trading.

The profitability of the relative strength index tools (ORSI and TRSI) provides evidence that the live hog futures market is not weak form efficient. Since one possible source of market inefficiency would be the assimilation of market information over time, and the methods in this study depend on interday market inefficiency, an interesting direction for future research would be to look at price dependent trading models that utilize intraday price information. In addition to chopping up a days' prices into smaller units and using technical analysis methods like those utilized in this study, Market Profile would be an interesting tool to evaluate in future studies. Market Profile provides intraday prices and actual or estimated volume at each price. Market Profile information is provided by both the CBOT and CME and is made available through private vendors. J. Peter Steidlmayer (1989) developed Market Profile and wrote about it in a book, Steidlmayer on Markets. Additional information regarding Market Profile is also available from the Market Profile Society International, located on the Western Illinois University campus, Macomb, Illinois.

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