Xavier Garza-Gomez (USA), Massoud Metghalchi (USA)

The effects of financial modernization on market efficiency: the case of the Mexican stock market

Abstract

This paper tests market efficiency in the Mexican stock market. In particular, the authors study the effect that the financial modernization in the Mexican stock exchange that ended in year 1999 with the opening of the Mexican derivatives market (MexDer) played in the results of trading rules based on popular technical indicators. Preliminary results indicate that several indicators did indeed have predictive power and could discern recurring-price patterns for profitable trading for the 21-year sample used in the study. However, when the sample is split into two based on the introduction of financial futures trading in Mexico, the authors find that simple non-levered timing strategies that showed profits before the index futures were introduced become unprofitable after futures started trading, which suggests that the overall stock market became efficient after the Mexican stock market became more sophisticated. Nevertheless, timing strategies that take advantage of the leverage available via future contracts do produce significant profits above the buy-and-hold strategy despite a higher risk involved.

Keywords: emerging markets, market efficiency, stock market predictability, technical trading strategies, index futures introduction, leverage.
JEL Classification: C22, G14.

Introduction

Technical analysis (TA) has been developing into a more and more rigorous and sophisticated investment tool. As Gandolfi et al. (2008) point out, the mid 1980's typical graphical approach, mostly based on chart analysis, has been replaced by more computationally intensive and systematic methodologies, typical of algorithmic technical analysis.

Technical analysis is based on the idea that prices move in trends, which are determined by the changing attitudes of traders towards various economic, political and psychological forces. In this paper, we define technical analysis as a method of evaluating commodities and stock prices by analyzing statistics generated by market activities, volume, open interest, past prices, and various indicators based on prices and volumes. Technical analysts do not attempt to measure a security's intrinsic value; instead they look for patterns and indicators on the charts that will determine whether you should go long or short or stay neutral for any security.

The main opponent of technical analysis is the Efficient Market Hypothesis (EMH), postulated by Fama (1970). He basically defines an efficient financial market as one in which security prices always fully reflect the available information and since news by definition are unpredictable (arrives randomly), price changes will be unpredictable or follow a random walk. Advocates of the EMH argue that investors cannot drive profits above a buy-and-hold strategy using any trading rule that depends solely on past market information such as price or volume, implying that technical analysis is useless.

Early research on technical analysis tended to support EMH, yet the amount of research showing the benefits of using TA on markets outside of the US tended to tilt the balance in favor of technical analysis. After a while, the supporters of EMH reexamined their main implication to allow for the existence of inefficient markets but with the warning that any profits from technical analysis would disappear after adjusting for the inherent risk and transaction costs of implementing that active strategy, which are expected to be high in those markets.

This paper attempts to shed some light into this ongoing debate. Our approach is simple; we use data from the Mexican stock market for two periods: before and after the modernization of the Mexican stock exchange (MSE). The upgrading in the MSE started in 1995 with the establishment of an electronic trading platform denominated SENTRA. This platform started for fixed income securities and on 1996 started the move into equities. The process was not completed until January 11, 1999, the first day in which stock trading became totally electronic. The modernization of the MSE also included the establishment of the Mexican derivatives market (MexDer) on December 1998. Stock market index (IPC) futures were introduced in MexDer on April 1999.

This paper uses the start of IPC futures trading to define two sample periods and measures the performance of simple technical trading rules to try to time the MSE. The introduction of index futures and/or options into an emerging market is a signal that investors and institutions are mature enough to use derivatives to effectively manage/control risk. With derivatives, investors can make money on the short side and effectively hedge any long-term holdings. Without derivatives, investors can only make money on the long side. Another advantage of introducing index futures in a stock market is a decrease in the stock market risk (see Gulen and Meyhew, 2000). Our sample period provides a good test of EMH in the sense that as investors become more sophisticated and markets evolve and provide more tools to manage risk, we would expect the anomalies found in emerging markets (extra profits for using technical analysis) would tend to disappear.

1. Literature review

1.1. Technical analysis. Early research on technical analysis overwhelmingly supported the "random walk" hypothesis or EMH (Larson, 1960; Osborne, 1962; Alexander, 1964; Granger and Morgenstern, 1963; Mandelbrot, 1963; Fama, 1965; Fama and Blume, 1966; Van Horn and Parker, 1967; Jensen and Benington, 1970).

Since the mid 1980s technical trading however has been enjoying a renaissance both on Wall Street and in academic circles. The cornerstones of these new researches were articles by Sweeney (1986), Lukac et al. (1988), and Brock et al. (1992). Sweeney (1986) applied filter rule techniques for ten currencies from 1973 to 1980 and found that various filters were profitable in more than 80 percent of the cases. Sweeney concluded that in one third of the cases the profits from trading rules were statistically significant. Lukac et al. (1987) find that during the 1978-1984 period, four technical trading rules, including moving average crossover, statistically beat the buy-and-hold strategy. Another important paper by Brock, Lakonishok and LeBaron (1992; BLL hereafter), analyzed moving averages and trading range breakouts in the Dow Jones Industrial Index from 1897 to 1985. Their work uses long moving averages of 50, 150 and 200 days with short averages of 1, 2 and 5 days to generate buy and sell signals. Drawing from their study, BLL point out that "all buy-sell differences are positive and the t-tests for these differences are highly significant…" and conclude that their "results are consistent with technical rules having predictive power". Other researchers have used BLL's moving averages techniques to investigate whether stock market indices can be predicted with some simple form of technical analysis. Bessembinder and Chan (1995) conclude that BBL's rules are profitable in Japan, Hong Kong, South Korea, Malaysia, Thailand and Taiwan, with the strongest predictability in the last three markets. Ergul, Holmes and Priestley (1997), using daily closing prices of 63 stocks traded on the Istanbul Stock Exchange, conclude that technical analysis on volume can aid the prediction of returns. Pruitt and White (1998), using the University of Chicago's CRSP daily data tapes over the 1976-1985 period, conclude that technical trading rules are capable of outperforming a simple buy-and-hold strategy even adjusting for transaction costs. Bessembinder and Chan (1998) confirm the basic BLL results; however, they argue that the BLL results can coexist with the notion of market efficiency when considering transaction costs. Fong and Ho (2001) use technical trading rules for internet stock and conclude that the average buy-sell spread is large and significant even after accounting for transaction costs. Gencay (1998a, 1998b) and Ratner and Leal (1999) also support the predictive power of technical trading rules. Metghalchi and Chang (2003) apply various moving average rules to the Italian stock index and conclude the profitability of technical trading over the buy and hold strategy. Chang et al. (2006) have used moving average trading rules for the Taiwan stock market and conclude that they have identified profitable trading strategies for that market over the time period of 1983-2002. Menkhoff and Taylor (2007, p. 949) survey a number of technical trading rules for currencies and conclude that "on balance, however, the literature of profitability of technical trading rules tends to support the existence of significant profits to be had by employing these rules in the foreign exchange markets". Lento (2007) examines the effectiveness of nine technical trading rules, including filter rules (momentum strategies) which generate buy and sell signals, in eight Asian-Pacific stock markets for periods ranging from January 1987 to November 2005. Metghalchi et al. (2008) use various moving average trading rules in the Swedish stock market and show that some moving average strategies could beat the buy-and-hold strategy even accounting for transaction costs and data snooping. Zhou and Zhou (2009), show that moving average rules add value to asset allocation strategies.

On the other hand, there are studies that do not support technical strategies. Raj and Thurston (1996) using moving average rules for the Hang Seng Futures Index conclude that the moving average strategy did not produce significant excess returns in that market. Hudson, Dempsey and Keasey (1996) apply BLL's technical trading rules in the United Kingdom stock market return over the 1935-1994 period and conclude that technical trading rules did not generate excess returns after taking transaction costs of 1 percent per round trip. Coutts and Cheung (2000) analyze the Hang Seng returns from 1985 to 1997 and conclude that both the moving average and trading breakout rules fail to provide positive abnormal returns, net of transaction costs. Taylor (2000) investigates many simple moving average rules for the UK and the U.S. stock indices and various individual stocks and finds that on the average the break-even one-way transaction cost is close to 0.35% across all data; this seems a bit low for profitable technical trading. In an excellent survey of technical trading rules for stock markets Park and Irwin (2007) categorize technical trading research into two categories: Early Studies (1960-1987) and Modern Studies (1988-2004). They conclude that in general the early studies of technical trading for stock markets show little evidence of profitability of technical trading rules. However, among a total of 95 modern studies, 56 find profitable trading rules, 20 show negative results, and 19 studies indicate mixed results. For surveys of technical trading in the foreign exchange market, Taylor and Allen (1992), Maillet and Michel (2000), and Menkhoff and Taylor (2007) provide an excellent summary of technical trading researches.

1.2. Effect of futures markets on cash markets. The introduction of a futures market for an asset that has no derivatives market is an important event that may help stabilize the cash market for that asset. The stabilization can be reflected by a reduction in the volatility and or an increase in the efficiency of the cash market. The literature studying the effect of index futures markets to the operation of stock markets shows some mixed evidence. When we look at studies in U.S. markets, Damodaran (1990) and Schwert (1990) suggest a higher volatility on the stock returns after the futures trading began but Santoni (1987) suggests a negative relation between futures volume and stock index volatility. Others, like Conrad (1989) suggest no significant impact on volatility while Edwards (1988) suggests a decrease in market volatility. McKenzie et al. (2001) find a reduction of risk in individual stocks after the listing of individual share future (ISFs). When we consider non-U.S. markets, we find increases in volatility in the UK (Kyriacou and Sarno, 1999), Japan (Lee and Ohk, 1992; and Chang et al., 1999) and Korea (Bae et al., 2004). On the other hand, Gulen and Mayhew (2000) analyzed a group of 25 countries and while they confirm an increase in volatility in the U.S. and Japan, they also report a significant overall decrease in cash market volatility for 16 countries. They suggest that the U.S. and Japan are the exception and not the rule.

The market efficiency in cash markets, which is related to many types of market frictions such as transaction costs, price change limits, restrictions on short selling, price rounding, market makers and investment ceilings (Cohen et al., 1986), can also be affected by the introduction of derivatives for the specific asset class. Cox (1976) notes that there are less frictions in the futures market than in the underlying spot markets. If futures prices are supposed to adjust quickly to new information and then transfer the effect to the spot market then market efficiency should be greater with the presence of the futures market than without its presence. Many of the tests of market efficiency have typically been made from the model $S_t = a + bF_{t-1,t} + e_t$, where efficiency would imply that $a = 0$ and $b = 1$ (see Elam and Dixon, 1988). This approach is subject to several methodological problems (see Elam and Dixon, 1988; Lai and Lai, 1991). Other tests of market efficiency include Chowdhury (1991) and Lai and Lai (1991), who use cointegration tests to assess the market efficiency and Bae et al. (2004), who test for efficiency for stocks included in a stock index. Other problems include the fact that testing for efficiency implies the assumption that there is no risk premium for futures investors. In this sense, most tests would involve a joint test of market efficiency and no-risk premium.

To circumvent the problems inherent in judging efficiency for futures and/or cash markets, this paper uses a simple approach. We test whether trading rules based on technical analysis can provide excess profits without an increase in portfolio risk before and after the modernization of the Mexican stock market. To assess whether the introduction of electronic trading and derivatives market improved the efficiency in the cash market, we will measure the amount of excess profits available before and after index futures started trading. Our approach thus provides a novel approach to test the effect of futures trading in the market efficiency of cash markets.

2. Methodology

2.1. Technical indicators used. Over the past two decades academicians have increasingly used the quantitative aspect of technical analysis that involves methods such as moving averages, filter rules, trading breakout, Bollinger bands, Stochastics, Relative strength Indicator (RSI), Moving Average Convergence Divergence (MACD) and many other rules. In this paper we will use a few of the most important technical indicators and their combinations. The first indicator used in this paper is the very well known moving average (MA) technique, the second indicator is the popular RSI indicator developed by Wells Wilder (1978). Our third indicator Parabolic Stop And Reverse (PSAR), is also developed by Wilder (1978); and finally the fourth indicator is the Moving Average Convergence Divergence Histogram (MACD), developed by Gerald Appel (1999). This paper extends the literature by exploring the effects of combining technical indicators when setting trading rules and by applying it to the Mexican stock market.

2.2. Data used in the study. We use daily closing level of the IPC index, an index constructed with the 35 most liquid stocks listed in the Mexican stock market (bolsa), over the period of July 1, 1988 to December 31, 2009. Since trading strategies require some observations to be calculated, all results are reported starting from January 1, 1989. For the risk free instrument we use the middle rate of the 1-day CETES. All data are collected from DataStream and are expressed in pesos. Although changes in stock price index do not include daily dividend yields, we do not expect this omission to alter the results of our analysis. Mills and Coutts (1995) review the literatures regarding dividends and conclude that any bias in the results due to dividend exclusion will be minimal. Draper and Paudyal (1997) also support this conclusion. Index futures for the IPC started trading on April 15, 1999 in the Mexican derivatives market (MexDer). We define our pre-futures sample from January 1989 to April 14, 1999 and the post-futures sample from April 15, 1999 to December 2009. As a robustness test we excluded the year of 1999 and compared 10 years before and 10 years after and the overall results and conclusions remain the same.

In Table 1 we compile the summary descriptive statistics for the whole period and two subperiods. From Table 1, we can point out some interesting facts; first the average daily returns are quite different for each subperiod. The average return on the first subperiod is about twice that of the second subperiod. The standard deviations for the two periods show a clear decrease from 1.70% to 1.56%, which is statistically significant. In a previous study of the Mexican stock index futures, Zhong et al. (2004) report that futures market was a source of instability for the spot market. The reduction in standard deviations we observe in the cash market in our sample differs from their findings. When we apply the Jarque-Bera test to the skewness and kurtosis reported in Table 1, we can say that the return distributions for the 3 samples are not normal. In addition the first order autocorrelation is positive but negative for the second and third orders. Overall, the economic environment is quite different for the two subperiods. On the first subperiod we have high interest rates and high stock market returns that accompanied the financial crisis of 1994. On the second subperiod, as interest rates decreased, the returns on the stock market also went down. Interestingly, when comparing the returns of stocks and the risk free instrument, the second subperiod, despite a lower absolute return, shows a much higher market premium.

2.3. Technical trading rules used. The moving average rule applied in this study is the crossing of moving average short and long. According to this rule, buy (sell) signals are emitted when the short-term moving average exceeds (is less than) the long-term moving average by a specified percentage (band). In this study we use long moving averages of 20, 30, 50, and 100. As for the short moving average, like the BLL study, we use 1 day (the raw price) moving average. Thus, a buy signal is emitted when the index level breaks the long one from below and a sell signal is emitted when the index level breaks the long from above. We assume that a trader following this strategy (and other strategies, PSAR, RSI, MACD) could presumably observe the index prices just before the day's close and enter a limit order to execute at market's closing price. In the case of the MA strategy, if the closing price is greater than the long moving average, then the trader will be in the market the next day by buying the index at the closing price (next day will be a buy day). Next day's return will be the difference between the logarithm of the closing price the next day and the logarithm of closing price the previous day. On the other hand, if the closing price is less than the long moving average, then we will sell the index at the closing price and will be out of the market the next day (next day will be a sell day meaning we will be out of the market).

We define P_t as the short moving average or the raw index level at time t, and define long moving average of M at time t as:

$$MA_t(M) = \frac{1}{M}\sum_{i=0}^{M-1} P_{t-i}. \tag{1}$$

We define the mean buy (X_B), the mean sell (X_S) and buy-and-hold (X_H) return as follows:

$$X_B = \frac{1}{N_B}\sum R_B, \tag{2}$$

$$X_S = \frac{1}{N_S}\sum R_S, \tag{3}$$

$$X_H = \frac{1}{N}\sum R, \tag{4}$$

where N_B (N_S) is the total number of buy (sell) days, N is the total number of observations (days), R_B (R_S) is daily returns on buy (sell) days; and R is the daily stock returns. We then perform three tests to analyze whether the mean buy returns and the mean sell returns of the MA rules are greater than the mean return of the buy-and-hold strategy and whether the mean return on buy days is greater than the mean return on sell days:

	Test 1	Test 2	Test 3
H_0:	$X_B - X_H \le 0$	$X_S - X_H \le 0$	$X_B - X_S \le 0$
H_A:	$X_B - X_H > 0$	$X_S - X_H > 0$	$X_B - X_S > 0$

Following Kwon and Kish (2002), the test statistic for the mean return on buy days over the mean buy-and-hold return (Test 1) is:

$$t = \frac{X_B - X_H}{\sqrt{VAR_B / N_B + VAR_H / N}}, \qquad (5)$$

Where VAR_B and VAR_H are the variances of buy and buy-and-hold returns, respectively. The above formula (5) is also used to test the mean sell return over the mean buy-and-hold return (Test 2) and the mean buy return over the mean sell return (Test 3) by replacing the appropriate variables in the t-statistic formula.

The second indicator used in this paper is the popular indicator created by Wells Wilder (1978), the Relative Strength Index (RSI). RSI is a ratio of the upward price movement to the total price movement over a given period of days (Wells Wilder suggested using 14). Suppose the number of days is *N*. The calculation of RSI is described below:

AU = Average of x days' up closes,

AD = Average of x days' down closes,

$$RSI = \frac{AU}{AU + AD} \times 100 .$$

RSI ranges from 0 to 100. Thus in this study a buy signal is emitted when the *RSI* is above 50, and we will be in the market as long as the RSI indicator is above 50. We will get out of the market as soon as the *RSI* goes below 50. Therefore, according to the RSI indicator we will be either in the market ($RSI >$ 50) or out of the market ($RSI <$ 50).

The third indicator is the Parabolic SAR (Stop and Reversal) Technical Indicator. The Parabolic SAR, developed by Wells Wilder, is generally used to set trailing price stops; thus it is a stop-loss system. The stop is continuously moved in the direction of the position. The indicator is below the price in a bull market (Up Trend), and when it's bearish (Down Trend), it is above the price. When the index is above the PSAR value, we will be in the market and when the index is below the PSAR value, we will be out of the market. PSAR values are calculated as follows:

$$PSAR_i + 1 = PSAR_i + AF \times \left(EP_i - PSAR_i\right),$$

where *PSARi* is the value of the indicator in the previous period; *AF* is the acceleration factor, it increases by 0.02 every time the extreme price is changed and capped at 0.20 as recommended by Wilder. *EPi*, or extreme price, is the highest (lowest) price for the previous period.

Finally the last indicator in this paper is the Moving Average Convergence Divergence Histogram. It is based on the popular MACD indicator developed by Gerald Appel. It is the difference between two exponential moving averages. In this paper we use 26 and 12 day moving averages as recommended by Gerald Appel. The MACD is calculated by subtracting the value of a 26-period exponential moving average from a 12-period exponential moving average. A 9-period simple moving average of the MACD (the signal line) is then plotted on top of the MACD.

$MACD = EMA(CLOSE, 12) - EMA(CLOSE, 26)$,

$Signal\ Line = SMA(MACD, 9)$,

$MACD - Histogram = MACD - Signal\ Line$,

where *EMA* is the exponential moving average and *SMA* is the simple moving average. The *MACD-Histogram* is the difference between the *MACD* and the signal line. The plot of this difference is presented as a histogram, making centerline crossovers (the zero line) easily identifiable. Again, in this study a buy signal is emitted when the *Histogram* is positive and we will be in the market as long as the *Histogram* stays positive. We will be out of the market as soon as the *Histogram* becomes negative. Therefore, according to *MACD-Histogram* indicator we will be either in the market or out of the market.

For the above three trading rules, we define mean buy and mean sell returns by equation (2) and (3); we then perform the three tests specified above to analyze whether the mean buy (sell) returns of each indicator is greater than the mean return of the buy-and-hold strategy and whether the mean return on buy days is greater than the mean return on sell days.

3. Empirical results

Table 2 summarizes the results of various technical indicators. For each rule we report mean returns on buy days, sell days, and buy minus sell days, standard deviations of returns on buy and sell days, and the percentage of buy and sell days. The numbers in the second row of each box are the t-statistics (equation (5)) testing the difference of the mean buy and mean sell from the unconditional daily mean, and buy-sell from zero.

The first row of Table 2 (see Appendix) reports results with trading rule MA(1, 20); we will be in the market (buy days) if the MA1 (Index level) is greater than MA20 and out of the market (sell days) if MA1 is less than or equal to MA20. The results of Table 2 show that all of the mean buy returns are positive and that 3 of them have significant t-statistics, rejecting the null hypothesis that the mean buy returns equal the unconditional 1-day return.

Trading rules of MA20, MA30 and RSI have the highest daily average returns in both sub periods; these trading rules produce higher averages on buy days than the buy-and-hold average. The MACDH and MA100 have the lowest returns on buy days on both sub periods. As for the sell days, the results are again good for MA20, MA30 and RSI on the first sub period but only MA30 and RSI reject the equality of the mean sell days with the unconditional 1-day return in the second subperiod. As for buy minus sell days, 6 rules in the first subperiod and 5 rules in the second subperiod are positive with significant t-statistics. Despite this partial support for the technical trading rules, we observe that the average difference between buy and sell days decreased by about 50%. For example for MA30, the difference was 0.36% in the first subperiod but only 0.18% in the second. This decrease is consistent with the assertion that the market became more efficient in the second subperiod. The standard deviations of daily returns of buy days and sell days are reported in Columns 5 and 6. The standard deviations for buy days are always smaller than those for sell days, implying that the market is less volatile for buy periods than sell periods. Columns 7 and 8 report the percentage of time that we obtain buy and sell signals. For example, across MA rules, an average 66 percent of the time we are in the market (buy days) and 34 percent out of the market (sell days). These percentages remain quite constant for the entire sample period suggesting that the basic operation of the technical rules didn't change.

We then estimated the mean buy days and sell days of trading strategies that combine two and three of the above indicators. Results are presented in Table 3. For two indicators, we combined MA20 and MA30, with PSAR and with RSI; and for three indicators we combined RSI and PSAR with MA20 and MA30. All of the equality tests (Test 3) of these combinations have highly significant t-statistics, rejecting the equality of returns on buy and sell days in the first subperiod. However for the second subperiod, we see a drastic reduction in the buy day returns, sell day returns as well as the buy-sell difference. In fact, in the second subperiod, none of the t-statistics for buy days or sell days is statistically significant. Only the average buy-sell turns out significant for 5 rules but with much lower values than those in the first subperiod. The best trading rule combination is MA30 and RSI. It performs well in both subperiods and outperforms all the 3-indicator rules and other 2-indicator rules.

If technical analysis is futile for forecasting price movements, as implied by EMH, then we should observe that the returns on buy-days do not differ appreciably from the returns on sell-days. However, the results of Table 2 and 3 indicate that some of the technical trading rules do indeed have predictive power and can discern recurring-price patterns that may be used for profitable trading. Given this predictive power of technical analysis, the next step is to put it to work with a trading strategy in order to compare it to the buy-and-hold strategy.

3.1. Basic trading strategies. Given that the mean buy is greater than the mean sell for most of our trading rules, the profitability of technical trading will depend on the how the buy/sell signals are put into practice by traders (trading strategy) and whether the excess returns obtained by each strategy exceed the transaction costs caused by trading. Two elements define the strategy: what the trader does on buy days and what the trader does on sell days. The simplest strategy that can be used is to be long in stocks on buy days and hold cash on sell days. If the trader does not invest on the sell days, then the trader's return on those days will be zero, which will result in a mean return of $(Nb/N)*X(b) + (Ns/N)*0$ for this strategy. Two other possibilities for sell days are to invest in the risk free instrument on days identified as "sell" or to sell short the stock index.

We define our first testable strategy as long/money, where the trader will be in the stock market when trading rules emit buy signals and will be in the money market when it emits sell signals (long/money). Since short sales are not allowed in the Mexican stock market and the use of leverage was quite restricted before 1999, we limit the strategies in this sub period to those that could have been employed by a trader in the local market.

For each trading rule we estimate the daily return and then subtract from it the daily return from a buy-and-hold strategy to get the daily return difference. To test whether the average daily return difference is greater than zero, we express the null and alternative hypotheses as follows:

$H_0 : ddif \leq 0,$

$H_A : ddif > 0.$

The t-statistic for the above test is:

$$t = \frac{X(ddif)}{\sqrt{Var(ddif)/N}}, \quad (6)$$

where $X(ddif)$ is the average daily return difference of each strategy over the buy-and-hold strategy and $Var(ddif)$ is the variance in the daily difference of returns, and N is the total number of days. Table 4 reports the results for some of the best technical trading rules of Table 2 and 3.

The results of Table 4 (see Appendix) suggest a strong predictive power of technical trading rules for the first subperiod. All six trading rules except for PSAR have highly significant p-values; therefore rejecting the hypothesis that the average return of these 5 technical trading rules are less than or equal to the buy-and-hold strategy. The frequency of trades produced by the rules goes from 9 to 20 trades per year. Single indicator strategies show higher frequencies than strategies based on 2 or more indicators. This result by itself suggests that the use of two or more indicators is useful to eliminate the number of false signals produced when only one indicator is used. In general, our results support the idea that more indicators should be used to confirm a change in trend that is the basis of a technical trading system. Requiring more indicators to get a sell signal will produce less trades and it will take longer for the system to switch from buy to sell or vice versa. Nevertheless, the annual excess returns (column 3) obtained by one-indicator rules are higher than those obtained with rules based on two or more indicators, which suggests that if a trader waits until 2 or more signals confirm the change of the trend, he (she) will be late and therefore miss a part of the potential profits. These opposing results illustrate the tradeoff of being early and risk false signals vs. being late and risk losing part of the profits that will exist in any active trading system. Results shown in Table 4 support the existence of this tradeoff.

In order to judge competing trading rules and determine if these trading strategies can beat a buy-and-hold strategy we have shown in column 7 the "break-even" transaction costs, which are the percentage one-way costs that eliminate the additional return obtained from technical trading (see Bessembinder and Chan, 1998). These numbers represent the profit (excess return) obtained by the trading strategy each time that a trade is executed. The highest breakeven costs (potential profit per transaction) results were produced by the MA30 and PSAR combination in the first subperiod and by the MA30 rule in the second subperiod and not by the rule producing the highest excess return. That is, the strategies with the highest excess returns don't produce the highest breakeven costs due to their higher number of transactions per year.

To judge whether the trading strategies beat the buy-and-hold benchmark, these breakeven costs must be compared to the real transaction costs incurred in active trading. If a trader's one-way transaction cost is below the break-even transaction costs of Table 4, the trader can use technical trading rules and beat the buy and hold strategy even after considering transaction costs. Domowitz et al. (2001) estimated the total transaction cost for 42 countries. Their calculations include slippage, commission and fees incurred in frequent trading and their estimate of the one-way transaction cost for Mexico is 61.7 basis points or 0.62 %. From the first panel of Table 4 we see that 4 strategies produce breakeven costs around 1.5%. This level is high and suggests the possibility to earn extra returns from active trading. We believe that Domowitz number is a good estimate after 1999 but it is probably too low to be used as benchmark for our first subperiod. Nevertheless, using a more conservative estimate of 1.25% (double the number suggested by Domowitz) our results show that several technical trading rules would be profitable for investors. The second subperiod included some drastic changes in the investment environment in Mexico. In addition to the start of the index futures market, trading became fully electronic, online brokers started to appear and the commissions and fees charged by brokers decreased significantly. When we repeat our tests for the subperiod after the futures market opened, we observe that all the breakeven costs fall drastically. None of them exceeds Domowitz' estimate for transaction cost of 0.62% which suggests that any advantage provided by technical analysis would be eliminated by the high transaction costs. Evidence in Table 4 is supportive of the efficient market hypothesis in the Mexican stock market in the subperiod after the modernization of the stock exchange.

To further illustrate the differences across the 2 subperiods, we include Figure 1, which shows the year-by-year breakeven costs for 2 of the best strategies tested in this study. We see in the chart that after the introduction of futures the average gain per transaction (breakeven cost) is much lower. It goes from 2% to just 0.5%, a statistically significant drop. Furthermore, before the modernization, we see 8 years (out of 10) of positive BE costs but in the 10 years after futures were introduced, only 5 have positive BE costs, a significant reduction in the likelihood of making money using technical analysis. We conclude that all the efforts in modernizing the Mexican stock exchange have made the stock market more efficient.

3.2. Levered trading strategies. Tests so far have been presented for trading strategies that are long stocks in buy days and long money market in sell days. This method is the only one that can be used in the period prior to the introduction of index futures because of the trading restrictions existent in the Mexican stock market. However, after the introduction of futures in 1999, we can test a second trading strategy normally used in the literature (see Bessembinder and Chan, 1998) which assumes that traders will borrow at the money market rate in order to double the investment in stocks when trading rules emit buy signals and will be in the money market when it emits sell signals (we label it leverage/money). This strategy has a trading return on buy days of $TR_t = 2 \times R_t - M_t$, and a return of M_t on sell days, where R_t is the index return on day t and M_t is the daily money market rate. Other strategies commonly used in the literature are Long/Short (long stocks on buy days and short on sell days) and Leverage/Short.

An important empirical issue when comparing different active strategies is to account for the risk created by the different trading rules. A Long/Money Market normally reduces risk to the trader because the time exposure to the market is less than 100%. Any reduction in the number of days invested in the market leads to a lower total risk and consequently a lower expected return. When an active strategy is capable to produce higher returns with lower risk, that finding becomes a severe anomaly that strongly contradicts EMH. Since these opportunities are extremely attractive to traders and investors, any such occurrence will tend to disappear as soon as enough people try to take advantage of it.

In this last section of the paper we present results for tests of 4 different trading strategies to explore whether the apparent inefficiency found in the first subperiod could be exploited with more advanced trading strategies. Panel A shows results for Long/Short and Panels B, C and D show results of using different degrees of leverage in buy days while keeping money market instrument in sell days. For these tests, we assume that the active trader will engage in futures trading that will enable him to modify his exposure to the market to the desired level. With the use of margin in the futures account, traders can easily multiply their market exposure by many times yet we have limited our tests to 2X, 3X and 4X the market.

The first panel (Long/short) shows that this strategy produces breakeven costs much lower than the simple Long/money market strategy. Furthermore, the standard deviation is much higher. The risk is about the same as being long 100% of the time. The combined evidence or higher risk and lower excess returns shows that selling stocks short on sell days is not attractive at all. For the rest of the tests, we refrained from shorting the market.

The levered tests show an important relationship. As leverage increases, the excess annual return and the risk (measured as standard deviation) increase but the breakeven cost barely improves. For 2X leverage, the highest breakeven cost is 1.02%, for 3X leverage, it is 1.06% and for 4X it is 1.22%. These values were obtained assuming that the transaction costs increase proportional to the leverage used. Though the improvement of increasing leverage looks discouraging, we believe that using futures to achieve X level of exposure in the stock market is subject to a transaction cost much lower than the 0.62% used above. If a trader pays 0.25% per one-way transaction, the profit per trade can be 0.75%. This amount multiplied by the amount of leverage could produce attractive returns to those traders willing to accept the inherent higher risk of such strategy. Overall evidence in Table 5 (see Appendix) does suggest the possibility that technical analysis can help investors achieve returns higher than the buy-and-hold strategy for the subperiod after index futures started trading. Nevertheless, consistent with EMH, these higher returns come with higher levels of risk. Because the high return comes at the expense of a higher risk, this is in no way a "free lunch" or an "anomaly". In fact, we wouldn't be surprised to see this finding endure for a long time and to be found in other stock markets around the world.

Conclusion

In this paper we investigate the performance of technical trading rules applied in the Mexican stock market before and after the modernization of the Mexican stock exchange. Overall findings are consistent with the idea that the Mexican stock market was inefficient in the 10 years before the modernization of the MSE and that the inefficiency disappeared after 1999. This paper used the date that index futures started trading to divide the entire sample in two because we consider that the introduction of index futures marked the end of the modernization efforts of the MSE and defined a new era for Mexican investors.

The empirical results provide evidence that in the 10 years before index futures were introduced, several technical indicators produced abnormal returns in excess of the buy-and-hold strategy, which suggests inefficiency in the Mexican stock market at that time. When we try to replicate the results over the 10 years after the index futures were introduced our results indicate that the benefits of technical analysis disappear after transaction costs are taken into account. However, we recognize that the introduction of index futures is not the only factor causing the increased efficiency. The index futures were the culmination of a broad modernization effort that included the switch to electronic trading, new regulations and the appearance of online brokers, all of which brought a greater participation of foreign investors and subsequently higher efficiency.

Among our findings we report that trading strategies based on combinations of technical indicators produce lower number of trades, which in general, improves the breakeven costs of the strategies.

Results also suggest that the use of index futures to increase the leverage in the trading account automatically increases the potential gains of technical analysis but at the expense of a higher trading risk. This potential benefit depends on the real transaction cost that the trader is subject to and his willingness to accept the higher risk. Since this benefit is achieved by accepting higher risk, our findings are consistent with the efficient market hypothesis.

References

1. Alexander S. (1964). "Price Movements in Speculative Markets: Trends or Random Walks", *Industrial Management Review*, 2, pp. 25-46.
2. Appel, G. (1999). *Technical Analysis Power Tools for Active Investors*, Financial Times Prentice Hall, p. 166.
3. Bae S.C., Kwon T.H. and Won J. (2004). Futures trading, spot market volatility, and market efficiency: The case of the Korean index futures markets, *Journal of Futures Markets*, Volume 24, Issue 12, pp. 1195-1228.
4. Bessembinder H. and Chan K. (1995). "The Profitability of Technical Trading Rules in the Asian Stock Markets, *Pacific-Basin Finance Journal*, 3, pp. 257-284.
5. Bessembinder H. and Chan K. (1998). "Market Efficiency and Returns to Technical Analysis", *Financial Management*, 27 (2), pp. 5-17.
6. Brock W., Lakonishok, J., and LeBaron B. (1992). "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns", *Journal of Finance*, 47, pp. 1731-1764.
7. Chang E.C., Cheng J.W. and Pinegar J.M. (1999). Does futures trading increase stock market volatility? The case of the Nikkei stock index futures markets, *Journal of Banking & Finance*, Volume 23, Issue 5, pp. 727-753.
8. Chang. Y., Metghalchi M. and Chan C. (2006). "Technical Trading Strategies and Cross-national Information Linkage: The Case of Taiwan Stock Market", *Applied Financial Economics*, Vol. 16, pp. 731-743.
9. Chowdhury A.R. (1991). Futures market efficiency: evidence from cointegration tests, *Journal of Futures Markets*, Volume 11, Issue 5, pp. 577-589.
10. Cohen, K., Maier, S., Schwartz, R. & Whitcomh, D. (1986). Inside the microstructure of securities markets, Englewood Cliffs, NJ: Prentice Hall.
11. Conrad, J. (1989). The price effect of option introduction, *Journal of Finance*, 44, pp. 487-498.
12. Coutts A. and Cheung K.C. (2000). "Trading rules and stock returns: some preliminary short run evidence from the Hang Seng 1985-1997", *Applied Financial Economics*, 10, pp. 579-686.
13. Cox, C.C. (1976). Futures trading and market information, *Journal of Political Economy*, 84, pp. 1215-1237.
14. Damodaran, A. (1990). Index futures and stock market volatility, *Review of Futures Markets*, 9, pp. 442-457.
15. Domowitz, I., Glen J. and A. Madhaven (2001). "Liquidity, Volatility, and Equity Trading Costs Across Countries and Over Time", *International Finance*, 4 (2), pp. 221-255.
16. Draper P. and Paudyal K. (1997). "Microstructure and seasonality in the UK equity market", *Journal of Business Finance and Accounting*, 24, pp. 1177-1204.
17. Edwards F.R. (1988). Does Futures Trading Increase Stock Market Volatility? *Financial Analysts Journal*, Vol. 44, No. 1 (January-February), pp. 63-69
18. Elam E. and Dixon B.L. (1988). Examining the validity of a test of futures market efficiency, *Journal of Futures Markets*, Volume 8, Issue 3, pp. 365-372.
19. Ergul A. Holmes P., and Priestley R. (1997). "Technical Analysis, Trading Volume and Market Efficiency: Evidence from an Emerging Market", *Applied Financial Economics*, 7, pp. 361-365.
20. Fama E. and Blume M. (1966). "Filter Rules and Stock Market Trading Profits", *Journal of Business*, 39, pp. 226-341.
21. Fama E. (1965). "The Behavior of Stock Market Prices", *Journal of Business*, 38, pp. 34-105.
22. Fama E. (1970). "Efficient Capital Markets: A review of theory and empirical work", *Journal of Finance*, 25, pp. 383-417.
23. Fong W.M. and Ho Y.W. (2001). "Simple Trading Rules and the Market for Internet Stocks", *International Review of Finance*, 2 (4), pp. 247-268.
24. Gandolfi G., M. Rossolini, A, Sabatini S. Caelli (2008). Dynamic MACD: Standard Deviation Embedded in the MACD Indicator for Accurate Adjustment to Financial Market dynamics, *International Federation of Technical Analysis Journal*, pp. 15-21.
25. Gencay R. (1998a). "Optimization of Technical trading strategies and profitability in Security Markets", *Economics Letters*, 59 (2), pp. 249-254.
26. Gencay R. (1998b). "The Predictability of Security Returns with Simple Technical Trading Rules", *Journal of Empirical Finance*, 5 (4), pp. 347-359.
27. Granger C. and Morgenstern O. (1963). "Spectral Analysis of New York Stock Market Prices", *Kyklos*, 16, pp. 1-27.
28. Gulen H. and Mayhew S. (2000). Stock index futures trading and volatility in international equity markets, *Journal of Futures Markets*, Volume 20, Issue 7, pp. 661-685.
29. Hudson R., Dempsey M., and Keasey K. (1996). "A Note on weak Form of Efficiency of Capital Markets: The Application of Simple Technical trading Rules to UK Stock Prices – 1935 to 1994", *Journal of Banking and Finance*, 20, pp. 1121-1132.
30. Jensen M. and Benington G. (1970). "Random Walks and Technical Theories: Some Additional Evidence", *Journal of Finance*, 25, pp. 469-82.

31. Kwon K. and Kish R. (2002). "Technical Trading Strategies and Return Predictability: NYSE", *Applied Financial Economics*, 12, pp. 639-653.
32. Kyriacou, K. and Sarno, L. (1999). The temporal relationship between derivatives trading and spot market volatility in the UK: Empirical analysis and Monte Carlo evidence, *Journal of Futures Markets*, 19, pp. 245-270.
33. Lai K. S. Lai M. (1991). A cointegration test for market efficiency, *Journal of Futures Markets*, Volume 11, Issue 5, pp. 567-575.
34. Larson A. (1960). "Measurement of Random Process in Futures Prices", *Food Research Institute*, 1, pp. 313-24.
35. Lee, S.B. and Ohk, K.Y. (1992). Stock index futures listing and structural changes in time-varying volatility, *Journal of Futures Markets*, 12, pp. 493-509.
36. Lento, C. (2007). Tests of Technical Trading Rules in the Asian-Pacific Equity Markets: A Bootstrap Approach. *Academy of Accounting & Financial Studies Journal*, 11 (2), pp. 51-73.
37. Lukac, L.P., B.W. Brorsen, and S.H. Irwin (1988). "A Test of Futures Market Disequilibrium Using Twelve Different Technical Trading Systems", *Applied Economics*, 20, pp. 623-639.
38. Maillet B. and Michel T. (2000). "Further Insights on the Puzzle of Technical Analysis Profitability", *The European Journal of Finance*, 6, pp. 196-224.
39. McKenzie M.D., Brailsford T.J. and Faff R.W. (2001). New insights into the impact of the introduction of futures trading on stock price volatility, *Journal of Futures Markets*, Volume 21, Issue 3, pp. 237-255.
40. Mandelbrot B. (1963). "The Variation of Certain Speculative Prices", *Journal of Business*, 36, pp. 394-419.
41. Menkhoff L. and M. Taylor (2007). "The Obstinate Passion of Foreign Exchange Professionals: Technical Analysis", *Journal of Economic Literature*, Vol. 45, Issue 4, pp. 936-972.
42. Metghalchi M. and Chang Y. (2003). "Profitable Technical Trading Rules for the Italian Stock Market", *Rivista Internationale Di Scienze Economiche e Commerciali*, Vol. L, No.4, pp. 433-450.
43. Metghalchi M., Chang Y. and Y. Marcucci (2008). "Is the Swedish Stock Market Efficient? Evidence From some simple Trading Rules", *International Review of Financial Analysis*, Vol. 17, Issue 3, pp. 475-490.
44. Mills T.C. and Coutts J.A. (1995). "Calendar effects in the London Stock Exchange FT-SE Indices", *European Journal of Finance*, 1, pp. 79-93.
45. Osborne M. (1962). "Periodic Structure in the Brownian Motion of Stock Prices", *Operations Research*, 10, pp. 345-79.
46. Park, C.H., and S.H. Irwin (2007). "What Do We Know about the Profitability of Technical Analysis?", *Journal of Economic Surveys*, 21 (4), pp. 786-826.
47. Pruitt S. and White R. (1998). "The CRISMA Trading System: Who Says Technical Analysis Can't Beat the Market?", *Journal of Portfolio Management*, 14 (3), pp. 55-58.
48. Raj M. and Thurston D. (1996). "Effectiveness of simple technical trading rules in the Hong Kong futures markets", *Applied Economics Letters*, 3, pp. 33-36.
49. Ratner M. and Leal R.P.C. (1999). "Test of Technical Trading Strategies in the Emerging Equity Markets of Latin America and Asia", *Journal of Banking and Finance*, 23 (1), pp. 1887-1905.
50. Santoni, G.J. (1987). Has programmed trading made stock prices more volatile? Federal Reserve Bank of St. Louis Review, pp. 18-29.
51. Schwert, G.W. (1990). Stock market volatihty, *Financial Analysts Journal*, 46, pp. 23-34.
52. Sweeney, R. (1986). "Beating the Foreign Exchange Market", *Journal of Finance*, 41, pp. 163-182.
53. Taylor M. and Allen H. (1992). "The Use of Technical Analysis in the Foreign Exchange market", *Journal of International Money and Finance*, 11, pp. 304-314.
54. Taylor S.J. (2000). "Stock index and price dynamics in the UK and US: New Evidence from Trading Rules and statistical Analysis", *European Journal of Finance*, 6, pp. 39-69.
55. Van Horn J.C. and Parker G.C. (1967). "The Random Walk Theory: an Empirical Test", *Financial Analyst Journal*, 23, pp. 87-92.
56. Wilder, W. (1978). New Concepts in Technical Analysis, Trend Research.
57. Zhong M., Darrat A.F., Otero R. (2004). Price discovery and volatility spillovers in index futures markets: Some evidence from Mexico, *Journal of Banking & Finance*, Volume 28, Issue 12, pp. 3037-3054.
58. Zhou Y. and Zhou G. (2009). Technical Analysis: An Asset allocation Perspective on the Use of Moving Averages, *Journal of Financial Economics*, Vol. 92, pp. 519-544.

Appendix

Table 1. Summary statistics

	Whole period	1989-1999	1999-2009
Daily Avg. Return	0.096%	0.126%	0.067%
Daily SD	1.63%	1.70%	1.56%
Geometric Annual Return	28.6%	36.4%	18.5%
End of period value of 1 peso	151.09	24.08	5.06
Skewness	-0.011	-0.10	0.09
Kurtosis	5.29	6.52	3.56
ρ_1	0.125*	0.136*	0.112*

Table 1 (cont.). Summary statistics

	Whole period	1989-1999	1999-2009
ρ_2	-0.032*	-0.014	-0.053
ρ_3	-0.017	-0.017	-0.019
Risk-free instrument			
Daily avg. return	0.070%	0.107%	0.033%
Daily SD	0.052%	0.052%	0.013%
Geometric annual return	20.4%	30.2%	8.7%
End of period value of 1 peso	39.64	14.51	1.3
Market vs. risk free			
Market premium	8.2%	6.2%	9.8%
Multiplier effect	3.8	1.7	3.9

The stock index for the Mexican stock market is the IPC, an index constructed with the most liquid stocks. The risk-free instrument is the 1-day middle rate of CETES. Sample period starts on January 1, 1989 and ends on December 31, 2009. Sample was split based on the day that futures were introduced in Mexico (April 15, 1999). Asterisks denote statistical significance at the 5% level for a one-tailed test ($t_{crit.,0.05} = 1.645$).

Table 2. Results for trading rules based on one technical indicator

Rules	Buy	Sell	Buy-sell	SD_b	SD_s	Buy days	Sell days
Before futures were introduced							
P vs. MA 20	0.26% 2.42	-0.09% -2.86	0,35% 5.13	1.39%	2.08%	61%	39%
P vs. MA 30	0.26% 2.38	-0.10% -2.98	0.36% 5.23	1.39%	2.10%	64%	36%
P vs. MA 50	0.21% 1.48	-0.03% -1.97	0.24% 3.37	1.36%	2.22%	67%	33%
P vs. MA 100	0.16% 0.63	0.04% -1.02	0.12% 1.63	1.40%	2.29%	72%	28%
P vs. PSAR	0.20% 1.32	0.02% -1.48	0.18% 2.71	1.43%	2.02%	59%	41%
RSI vs. 50	0.24% 2.08	-0.08% -2.64	0.32% 4.60	1.38%	2.14%	64%	36%
MACD hist vs. 0	0.17% 0.74	0.05% -1.01	0.12% 1.70	1.42%	2.14%	67%	33%
After futures were introduced							
P vs. MA 20	0.13% 1.26	-0.04% -1.62	0.17% 2.64	1.31%	1.93%	64%	36%
P vs. MA 30	0.13% 1.36	-0.05% -1.80	0.18% 2.91	1.29%	1.98%	66%	34%
P vs..MA 50	0.11% 0.93	-0.02% -1.22	0.12% 1.97	1.28%	1.99%	66%	34%
P vs. MA 100	0.10% 0.75	0.00% -0.97	0.10% 1.58	1.28%	1.99%	66%	34%
P vs. PSAR	0.11% 0.93	0.00% -1.09	0.11% 1.83	1.35%	l.83%	60%	40%
RSI vs. 50	0.13% 1.44	-0.06% -1.90	0.19% 3.07	1.30%	1.96%	65%	35%
MACD hist vs. 0	0.09% 0.43	0.03% -0.59	0.06% 0.93	1.28%	2.01%	67%	33%

Sample period starts on January 1, 1989 and ends on December 31, 2009. Sample was split based on the day that futures were introduced in Mexico (April 15, 1999). The first column identifies technical trading rules. Buy and sell are the daily average returns during the buy and sell days. SD_b and SD_s are daily standard deviation during buy and sell days. Last 2 columns show the percentage of buy and sell days. The numbers in the second row are the t-statistics testing the difference of the mean buy and mean sell from the unconditional 1-day mean, and buy-sell from zero.

Table 3. Results for trading rules based on two or more technical indicators

Rules	Buy	Sell	Buy-sell	SD_b	SD_s	Buy days	Sell days
Before futures were introduced							
MA20, PSAR	0.23% 1.89	-0.04% -2.17	0.27% 3.93	1.40%	2.06%	60%	40%
MA30, PSAR	0.23% 1.95	-0.06% -2.45	0.30% 4.29	1.40%	2.11%	64%	36%

Table 3 (cont.). Results for trading rules based on two or more technical indicators

Rules	Buy	Sell	Buy-sell	SD_b	SD_s	Buy days	Sell days
MA20, RSI	0.23% 1.91	-0.06% -2.38	0.29% 4.17	1,39%	2.12%	63%	37%
MA30, RSI	0.25% 2.20	-0.09% -2.79	0.34% 4.86	1.40%	2.10%	64%	36%
MA20, PSAR, RSI	0.21% 1.51	-0.01% -1.82	0.22% 3.23	1.39%	2.10%	62%	38%
MA30, PSAR, RSI	0.23% 1.90	-0.06% -2.38	0.29% 4.17	1.40%	2.10%	63%	37%
After futures were introduced							
MA20, PSAR	0.10% 0.79	0.00% -0.97	0.10% 1.61	1.32%	1.90%	63%	37%
MA30, PSAR	0.11% 1.03	-0.02% -1.33	0.14% 2.16	1.29%	1.96%	65%	35%
MA20, RSI	0.12% 1.15	-0.03% -1.52	0.15% 2.45	1.30%	1.97%	66%	34%
MA30, RSI	0.12% 1.16	-0.04% -1.53	0.16% 2.47	1.28%	1.99%	66%	34%
MA20, PSAR, RSI	0.11% 0.85	-0.01% -1.09	0.11% 1.78	1.29%	1.97%	65%	35%
MA30, PSAR, RSI	0.12% 1.05	-0.02% -1.36	0.14% 2.22	1.29%	1.96%	65%	35%

Sample period starts on January 1, 1989 and ends on December 31, 2009. Sample was split based on the day that futures were introduced in Mexico (April 15, 1999). The first column identifies technical trading rules. Buy and sell are the daily average returns during the buy and sell days. SD_b and SD_s are daily standard deviation during buy and sell days. Last 2 columns show the percentage of buy and sell days. The numbers in the second row are the t-statistics testing the difference of the mean buy and mean sell from the unconditional 1-day mean, and buy-sell from zero.

Table 4. Results of applying technical trading rules to a long/money market strategy

	X(*ddiff*)	Annual excess return	p-value	Total number of transactions	Transactions per year	One-way breakeven costs	Daily standard deviation
Before futures were introduced							
MA30	0.075%	20.5%	0.001	144	13.9	1.47%	1.11%
PSAR	0.035%	9.0%	0.085	206	19.9	0.45%	1.10%
RSI	0.066%	17.6%	0.005	190	18.3	0.96%	1.11%
MA30, PSAR	0.060%	16.0%	0.009	98	9.4	1.69%	1.12%
MA30, RSI	0.069%	18.7%	0.003	130	12.5	1.49%	1.12%
MA30, PSAR, RSI	0.059%	15.5%	0.010	96	9.3	1.68%	1.12%
After futures were introduced							
MA30	0.032%	8.5%	0.076	159	15.0	0.57%	1.04%
PSAR	0.015%	4.0%	0.245	221	20.8	0.19%	1.05%
RSI	0.034%	9.1%	0.061	197	18.5	0.49%	1.05%
MA30, PSAR	0.021%	5.5%	0.172	111	10.4	0.53%	1.04%
MA30, RSI	0.026%	6.8%	0.124	143	13.5	0.50%	1.04%
MA30, PSAR, RSI	0.022%	5.7%	0.163	109	10.3	0.56%	1.04%

X(*ddif*) is the average of daily difference between the return of each strategy and the buy-and-hold strategy. Annual excess return is the theoretical gain obtained by the trading strategy calculated as EXP(*X*(*ddif*) x # *trading days*) – 1. P-value is obtained from testing whether *X*(*ddiff*) is different from zero. Number of transactions represents the number of times each strategy gets in and out of the market. It is also reported per year *t*. Breakeven costs are estimated by the ratio of annual excess return over trades per year. SD are calculated for the returns of applying the trading strategy. All numbers are obtained from being long stocks on buy days and being in money market in sell days.

Table 5. Results of applying technical trading rules to strategies involving short sales and/or leverage

	X(*ddiff*)	Annual excess return	p-value	Total number of transactions	Transactions per year	One-way breakeven costs	Daily standard deviation
Long (X1) and Short							
MA30	0.031%	8.2%	0.205	159	15.0	0.27%	1.54%
PSAR	-0.008%	-2.0%	0.491	221	20.8	-0.05%	1.54%

Table 5 (cont.). Results of applying technical trading rules to strategies involving short sales and/or leverage

	X(ddiff)	Annual excess return	p-value	Total number of transactions	Transactions per year	One-way breakeven costs	Daily standard deviation
RSI	0.038%	10.0%	0.166	197	18.5	0.27%	1.54%
MA30, PSAR	0.009%	2.4%	0.362	111	10.4	0.11%	1.54%
MA30, RSI	0.019%	4.9%	0.288	143	13.5	0.18%	1.54%
MA30, PSAR, RSI	0.011%	2.9%	0.348	109	10.3	0.14%	1.54%
Leverage (X2) and money market							
MA30	0.095%	27.3%	0.001	159	15.0	0.91%	2.09%
PSAR	0.062%	17.0%	0.020	221	20.8	0.41%	2.09%
RSI	0.100%	28.8%	0.000	197	18.5	0.78%	2.10%
MA30, PSAR	0.073%	20.5%	0.007	111	10.4	0.98%	2.09%
MA30, RSI	0.083%	23.3%	0.003	143	13.5	0.87%	2.09%
MA30, PSAR, RSI	0.075%	21.0%	0.006	109	10.3	1.02%	2.09%
Leverage (X3) and money market							
MA30	0.141%	42.9%	0.001	159	15.0	0.96%	3.06%
PSAR	0.086%	24.5%	0.023	221	20.8	0.39%	3.07%
RSI	0.151%	46.7%	0.000	197	18.5	0.84%	3.07%
MA30, PSAR	0.109%	31.8%	0.006	111	10.4	1.02%	3.04%
MA30, RSI	0.122%	36.3%	0.003	143	13.5	0.90%	3.05%
MA30, PSAR, RSI	0.111%	32.7%	0.006	109	10.3	1.06%	3.04%
Leverage (X4) and money market							
MA30	0.199%	65.6%	0.001	159	15.0	1.10%	4.08%
PSAR	0.126%	37.8%	0.021	221	20.8	0.45%	4.10%
RSI	0.213%	71.6%	0.000	197	18.5	0.96%	4.10%
MA30, PSAR	0.156%	48.7%	0.006	111	10.4	1.17%	4.06%
MA30, RSI	0.174%	55.6%	0.003	143	13.5	1.03%	4.07%
MA30, PSAR, RSI	0.160%	50.0%	0.005	109	10.3	1.22%	4.06%

X(ddif) is the average of daily difference between the return of each strategy and the buy-and-hold strategy. Annual excess return is the theoretical gain obtained by the trading strategy calculated as EXP(*X(ddif) x # trading days*) – 1. P-value is obtained from testing whether *X(ddiff)* is different from zero. Number of transactions represents the number of times each strategy gets in and out of the market. It is also reported per year. Breakeven costs are estimated by the ratio of annual excess return over trades per year. Breakeven costs are adjusted to reflect the higher transaction paid in each trade. SD are for the returns of applying the trading strategy. All numbers are obtained for period after the index futures became available.

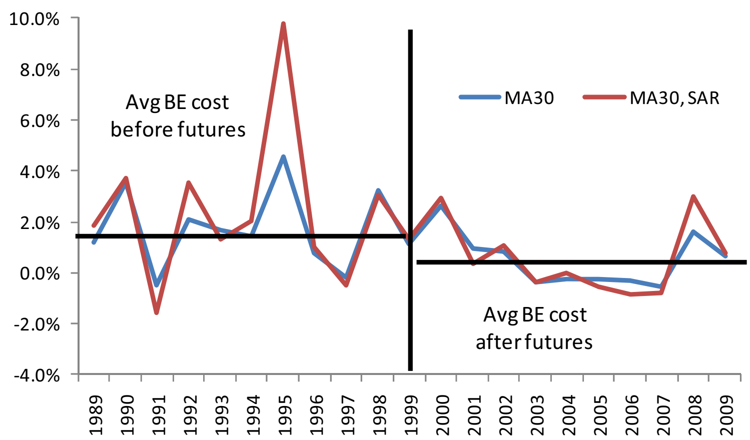

Fig. 1. Breakeven trading costs for two trading rules

Breakeven costs are calculated for each of the years in the sample by dividing the excess return created by the trading strategy beyond the buy-and-hold strategy divided by the number of trades in the year. Plot shows results for two trading rules (MA30 and the combination of MA30 and PSAR). Sample averages are shown in the figure.