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Abstract

This paper investigates how technical trading systems exploit the momentum and reversal effects in the S&P 500 spot and futures market. The former is exploited by trend-following models, while the latter by contrarian models. In total, the performance of 2580 widely used models is analyzed. When based on daily data, the profitability of technical stock trading has steadily declined since 1960 and has become unprofitable over the 1990s. However, when based on 30-minutes-data the same models produce an average gross return of 8.8% per year between 1983 and 2000. These results do not change substantially when trading is simulated over six subperiods. Those 25 models which performed best over the most recent subperiod produce a significantly higher gross return over the subsequent subperiod than all models. Over the out-of-sample-period 2001-2006 the 2580 models perform much worse than between 1983 and 2000. This result could be due to stock markets becoming more efficient or to stock price trends shifting from 30-minutes-prices to prices of higher frequencies.

Keywords: Technical trading, stock price dynamics, momentum effect, reversal effect

JEL classification: G12, G13, G14

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1. Introduction

In the recent debates over the informational (in)efficiency of the stock market, particular attention has been paid to two "anomalies," the momentum and reversal effects. The first effect refers to the phenomenon of stock price trends that can be profitably exploited by following "momentum strategies" (Fama-French, 1989; Jegadeesh-Titman, 1993; Chan-Jegadeesh-Lakonishok, 1996; Goetzmann-Massa, 2000); the second refers to reversals in stock price trends that can be profitably exploited following "contrarian strategies" (DeBondt-Thaler, 1985 and 1987; Fama-French, 1989; Jegadeesh, 1990; Lo-MacKinlay, 1990; Lehman, 1990).

All these studies investigate the profitability of hypothetical trading strategies that are not actually used by market participants. However, market participants use a great variety of trading techniques to exploit asset price trends and their reversals, i. e., the trend-following and contrarian models of technical analysis.

Technical analysis is omnipresent in financial markets. In the foreign exchange market, e. g., technical analysis is the most widely used trading technique (for recent survey studies see Taylor-Allen, 1992; Cheung-Wong, 2000; Cheung-Chinn, 2001; Oberlechner, 2001; Cheung-Chinn-Marsh, 2004; Gehrig-Menkhoff; 2004, 2005 and 2006; Menkhoff-Taylor, 2007). It seems highly plausible that technical analysis plays a similar role in stock markets, particularly in short-term trading in stock futures (Irwin-Holt, 2004, provide evidence about the popularity of technical analysis in futures markets).

The omnipresence of technical analysis in financial markets presents a dilemma for conventional asset market theory. If technical trading is not profitable, then the assumption of market participants' rationality is in doubt, whereas, if technical analysis is actually profitable, then the assumption of (weak-form) market efficiency is in doubt.

Many empirical studies of the performance of technical trading systems in the stock and foreign exchange markets report that these trading techniques would have been abnormally profitable.[1]) The results of these studies have not, on the whole, been taken seriously by the

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[1]) For stock market studies see Goldberg-Schulmeister (1988), Brock-Lakonishok-LeBaron (1992), Hudson-Dempsey-Keasey (1996), Gunasekarage-Power (2001), Fernandez-Rodriguez-Gonzalez-Martel-Sosvilla-Rivero (2000 and 2005), Kwon-Kish (2002), Wong-Manzur-Chew (2003), Jasic-Wood (2004), Chang-Metghalchi-Chan (2006). "Abnormal" returns of technical analysis in foreign exchange markets are reported by Schulmeister (1988), Levich-Thomas (1993), Menkhoff-Schlumberger (1995), Gencay-Stengos (1998), Chang-Osler (1999), Neely-Weller (1999), Gencay (1999), LeBaron (1999), Osler (2000), Maillet-Michel (2000), Neely-Weller (2003), Okunev-White (2003),

economists' profession. There might be several reasons for that. First, if one accepted the excessive profitability of technical analysis as a feature of asset markets then fundamental concepts like market efficiency or rational expectations would have to be seriously reconsidered. Second, recent studies – all based on daily data - find that the profitability of technical analysis has strongly declined or even ceased to exist in the stock market (Sullivan-Timmermann-White, 1999), in the foreign exchange market (Ohlson, 2004; Schulmeister, 2007A and 2007B) as well as in many futures markets (Park-Irwin, 2005). This could be viewed as confirmation that their excessive returns were only a temporary phenomenon. Finally, most of the extant studies report the profitability of only a relatively small number of trading rules and this gave rise to the suspicion of "data mining"; researchers might have been biased in favor of finding ex post profitable trading rules which a trader in practice would not know about ex ante.

The purpose of the present paper is to provide new insights into the performance of technical trading in the stock market. In particular, I re-examine the finding that the profitability of technical analysis has declined over the 1990s by analyzing the ex-post-profitability of 2580 moving average models, momentum models and relative strength models in the S&P 500 spot market (1960/2000) and in the stock index futures market (1983/2000). These models comprise trend-following as well as contrarian trading systems. My analysis is based on daily and 30-minute data.[2]) I find that the profitability of technical analysis prior to the 1990s was in fact not transitory. Rather, the type of technical models that is profitable has merely shifted from ones that are based on daily data to those that are based on higher frequency data. In particular, I find:

- The 2580 technical models tested would have produced an average gross rate of return of only 1.9% per year when trading in the S&P 500 spot market based on daily prices between 1960 and 2000. The profitability of these models has steadily declined from 8.6% per year (1960/71) to 2.0% (1972/82), -0.0% (1983/91) to –5.1% (1992/2000).
- The picture is very different for stock futures trading based on 30-minutes-data. The 2580 models produce an average gross return of 8.8% per year between 1983 and 2000. The contrarian models perform much better (10.9%) than the trend-following models (6.4%).

Beyond examining ex-post profitability, I analyze the structure of the profitability of these models and relate the results to the implied pattern in stock price dynamics. I also simulate the process of model selection based on their performance in the past and test for the ex-ante-profitability of the selected models. I find that:

- The profitability of technical stock futures trading is exclusively due to the exploitation of persistent price trends around which stock prices fluctuate.

Neely-Weller (2006), Schulmeister (2007A and 2007B). Excellent surveys of studies on technical analysis are Park-Irwin (2004) for all asset markets and Menkhoff-Taylor (2006) for the foreign exchange market.

[2]) In a second study I analyze the aggregate trading behavior of the same 2580 models in the S&P 500 futures market (Schulmeister, 2007C). In paricular, I explore how the concentration of transactions on buys/sell and of positions on long/short produced by technical trading systems impact upon stock price movements.

- Those 25 models which performed best over the most recent subperiod (ex post) produce a significantly higher gross return over the subsequent subperiod (ex ante) than all models in sample (18.7% and 9.6%, respectively).

When testing the same 2580 trading systems over the out-of-sample-period 2001-2006 (based on 30-minutes-data) it turns out that the models would have performed much worse than between 1983 and 2000. This result could be due to stock markets becoming more efficient or to stock price trends shifting from 30-minutes-prices to prices of higher frequencies.

2. How technical trading systems work

Technical analysis tries to exploit price trends which "technicians" consider the most typical feature of asset price dynamics ("the trend is your friend"). Hence, these trading techniques derive buy and sell signals from the most recent price movements which (purportedly) indicate the continuation of a trend or its reversal (trend-following or contrarian models).[3]) Since technical analysts believe that the pattern of asset price dynamics as a sequence of trends interrupted by "whipsaws" repeats itself across different time scales they apply technical models to price data of almost any frequency, ranging from daily data to tick data.

According to the timing of trading signals one can distinguish between trend-following strategies and contrarian models. Trend-following systems produce buy (sell) signals in the early stage of an upward (downward) trend whereas contrarian strategies produce sell (buy) signals at the end of an upward (downward) trend, e. g., contrarian models try to identify "overbought" ("oversold") situations.[4])

According to the method of processing price data one can distinguish between qualitative and quantitative trading systems. The qualitative approaches rely on the interpretation of some (purportedly) typical configurations of the ups and downs of price movements like head and shoulders, top and bottom formations or resistance lines (most of these approaches are contrarian, e. g., they try to anticipate trend reversals). These chartist techniques turn out to be profitable in many cases though less than moving average and momentum models (Chang-Osler, 1999; Osler, 2000; Lo-Mamaysky-Wang, 2000).

The quantitative approaches try to isolate trends from non-directional movements using statistical transformations of past prices. Consequently, these models produce clearly defined buy and sell signals, which can be accurately tested. The most common quantitative trading systems are moving average models, momentum models and the so-called relative strength index. These types of models are tested in the study. For a simple explanation of how these models work it is in the following section assumed that the models are applied to daily data.

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[3]) Kaufman (1987) provides an excellent treatment of the different methods of technical analysis; other textbooks are Murphy (1986), Pring (1991), Achelis (2001). The increasingly popular "day trading" based on technical models is dealt with in Deel (2000) and Velez-Capra (2000).

[4]) In the behavioral finance literature trend-following approaches are called "momentum strategies", however, in the remainder of this study they are termed "trend-following" since in the terminology of technical analysis "momentum" refers to a specific type of model which can be trend-following as well as contrarian.

2.1 Trend-following and contrarian versions of technical models

The first type of model consists of a (unweighted) short-term moving average (MAS_j) and a long-term moving average (MAL_k) of past prices. The length j of MAS usually varies between 1 day (in this case the original price series serves as the shortest possible MAS) and 10 days, the length k of MAL usually lies between 10 and 30 days.

The basic trading rule of average models is as follows (signal generation 1):

Buy (go long) when the short-term (faster) moving average crosses the long-term (slower) moving average from below and sell (go short) when the converse occurs. Or equivalently: Open a long position when the difference (MAS_j-MAL_k) becomes positive, otherwise open a short position. If one expresses this difference as percentage of MAL_k one gets the moving average oscillator:

$MAO(j,k)_t = [(MAS_{j,t}-MAL_{k,t})/MAL_{k,t}]*100$

This type of representation facilitates a (graphical) comparison of the signal generation between moving average models and momentum models.

The second type of model works with the relative difference (rate of change in %) between the current price and that i days ago:

$M(i)_t = [(P_t - P_{t-i})/ P_{t-i}]*100$

The basic trading rule of momentum models is as follows (signal generation 1):

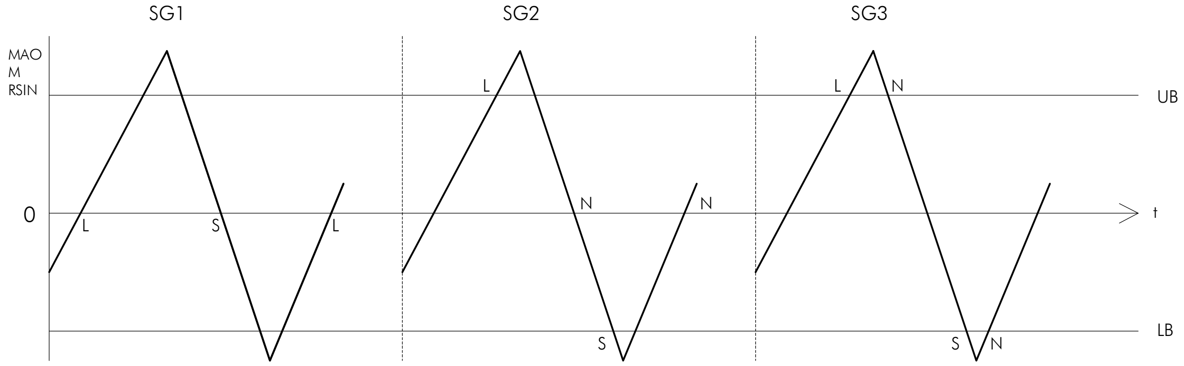
Buy (go long) when the momentum M(i) turns from negative into positive and sell (go short) in the opposite case.

The variables MAO(j,k) or M(i) are called "oscillators" because they fluctuate around zero.

The basic trading rule (SG 1) of moving average models and momentum models is trend-following since $MAS_{j,t}$ (P_t) exceeds (falls below) $MAL_{k,t}$ (P_{t-i}) only if an upward (downward) price movement has persisted for some days (depending on the lengths of the moving averages and the time span i in the case of momentum models, respectively).

The modifications of the basic version of moving average and momentum models use a band with varying width around zero combined with different rules of opening a long, short or neutral position (see, e. g., Kaufman, 1987, chapters 5 and 6). These rules – termed SG 2 to SG 6 in this study – are either trend-following or contrarian.

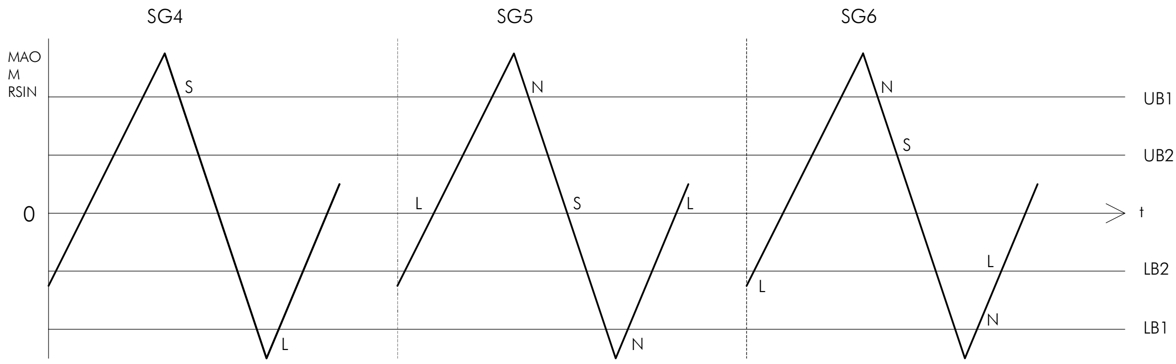
According to signal generation 2 one opens a long (short) position whenever the oscillator crosses the upper (lower) bound from below (above). When the model holds a long (short) position and the oscillator crosses the zero line from above (below) then the model switches to a neutral position. A simple graph may clarify the meaning of this rule by comparing it to SG 1:



Rule SG 2 is "more" trend-following than SG 1 since it opens a long or short position at a later stage of a price trend. At the same time SG 2 is more "cautious" than SG 1 since it always holds a neutral position between switching from long to short and vice versa.

Rule SG 3 differs from SG 2 insofar as the former switches from an open to a neutral position earlier. Whenever the oscillator crosses the upper (lower) band from above (below) rule SG 3 turns from long (short) to neutral. A momentum oscillator, e. g., closes a long position even if the current price still exceeds the price i days ago, provided that the (positive) rate of change $[(P_t - P_{t-i})/ P_{t-i}]*100$ is declining and falls below the level of the upper bound.

The trading rules SG 4 to 6 are contrarian since they try to identify "overbought" ("oversold") situations. An overbought situation is indicated when the oscillator is falling below a certain – still positive – level. If the oscillator is rising – though still negative – the situation is considered oversold once the oscillator crosses the lower bound from below. A simple graph shows the differences between the 3 contrarian trading rules:



Rule SG 4 is always either long or short (as is the trend-following rule SG 1). According to SG 4 a trader switches from a long (short) to a short (long) position once the oscillator crosses the upper (lower) bound from above (below). Hence, even if the rate of price change in the case of a momentum model is still positive the model SG 4 switches from a long to a short position once the rate of price change falls below the level of the upper bound.

Rule SG 5 is more "cautious" than SG 4 insofar as the former goes at first neutral when the oscillator penetrates the upper (lower) bound from above (below), and switches to a short (long) position only if the oscillator penetrates the zero line.

Rule SG 6 operates with a second (inner) band marked by UB2 and LB2 (UB1>UB2>LB2>LB1). This model holds a neutral position whenever a falling (rising) oscillator lies between UB1 and UB2 (LB1 and LB2) and, hence, is less often neutral as compared to SG 5. Rule SG 6 can be considered a combination of SG 4 and SG 5. At the extreme values of UB2 (LB2) the model SG 6 is identical either with SG 4 (when UB2=UB1 and LB2=LB1) or with SG 5 (when UB2=LB2=0).

One of the most popular indicators for identifying overbought and oversold conditions is the so-called Relative Strength Index (RSI). Since the strategy of following this index is contrarian only the trading rules SG 4 to SG 5 can be applied. The n-day RSI is defined as follows (Kaufman, 1987, p. 99).

$RSI(n)_t = 100 – \{100/[1+Up_t(n)/Down_t(n)]\}$

Where

D_i is the (daily) price change:

$D_i = P_{t-i+1} - P_{t-i}$ for i = 1…….n

And

$Up_t(n)$, $Down_t(n)$ are the average positive or negative price changes within the n-day interval.

$Up_t(n) = \Sigma D_i/n$ for $D_i>0$

$Down_t(n) = \Sigma D_i/n$ for $D_i<0$

The size of the RSI(n) oscillator does not only depend on the overall price change $P_t – P_{t-n}$ (as the momentum oscillator) but also on the degree of monotonicity of this change, e. g., the less countermovements occur during an upward (downward) trend the higher (lower) is RSI(n) for any given price change $P_t – P_{t-n}$. If the RSI(n) falls (rises) again below (above) a certain level (the upper/lower bound of the RSI oscillator) the situation is considered overbought (oversold).[5])

The original RSI fluctuates between 0 and 100. To make this oscillator comparable to the moving average and the momentum oscillator, respectively, one can calculate a normalized RSI (=RSIN) which fluctuates around zero:

$RSIN(n)_t = (1/100)*[RSI(n)_t – 50]*2$

The contrarian trading rules SG 4, SG 5 and SG 6 can then be applied to this normalized index in the same way as to the moving average oscillator and the momentum oscillator, respectively.

2.2 Model selection and profit calculation

The study investigates a great variety of technical models. In the case of moving average models all combinations of a short-term moving average (MAS) between 1 and 12 days and a long-term moving average (MAL) between 6 and 40 days are tested under the restriction

[5]) J. Welles Wilder who developed the Relative Strength Index favors a very specific application of this concept, e. g., a time span n of 14 days, an upper bound of 70 and a lower bound of 30 (Kaufman, 1987, p. 97). Later in practice traders have experimented with different time spans as well as different widths of the band (in this study two sizes of the upper and lower bound are tested, as well as 38 different time spans).

that the lengths of MAL and MAS differ by at least 5 days. This restriction excludes those models which produce too many signals due to the similarity of the two moving averages. Hence, 354 moving average models are tested for each of the six types of signal generation, in total 2.124 models. In the case of momentum models and RSIN models the time span runs from 3 to 40 days (38 models per type of signal generation).

As upper (lower) bound the value 0,3 (-0,3) is chosen for all types of models and trading rules. In the case of RSIN models also an upper (lower) bound of 0,4 (-0,4) is tested for the signal generation 4 to 6 (SG 1 to 3 are not used in the case of RSIN models) so that the number of RSIN models tested in this study is the same as the number of momentum models (228). In total, the performance of 2580 different technical trading systems is simulated in the study.

The main criterion for the selection of the parameter ranges was to cover those models that are used in practice. Hence the selection is based on informal interviews with stock dealers as well as on the literature on technical analysis (however, there remains always an ad hoc element since one cannot know the universe of all trading rules used in practice).

The simulation trading is based on the following assumptions. With regard to the market for stock index futures the most liquid contract is traded. Hence, it is assumed that the technical trader rolls over his open position on the 10th day of the expiration month from the near-by contract to the contact which is to expire three months later. In order to avoid a break in the signal generating price series the prices of the contract which expires in the following quarter is indexed with the price of the near-by contract as a base (software for technical trading in the futures markets also provide such "price shifts at contract switch"). This "synthetic" price series is, however, only used for the generation of trading signals, the execution of the signals is simulated on the basis of the actually observed prices.

When simulating the performance of daily trading systems the open price is used for both, the generation of trading signals as well as for the calculation of the returns from each position.[6]) Using open prices ensures that the price at which a trade is executed is very close to that price which triggered off the respective trading signal (this would not be the case if one used the daily close price).

Commissions and slippage costs are estimated under the assumption that the technical models are used by a professional trader for trading at electronic exchanges like Globex (Mini S&P 500 futures contract). This implies commissions per transaction of roughly 0.002%.[7]) Slippage costs are put at 0.008%.[8])

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[6]) When simulating the performance of daily trading systems in the S&P 500 futures market the price at 10 a.m. was used. These price data as well as the 30-minutes-data were extracted from the tick data base provided by the Futures Industry Institute (Washington, D.C.) for 1983/2000 and by ANFutures (http://www.anfutures.com) for 2001/2006.

[7]) Institutional traders pay roughly 10$ for a round trip in the S&P 500 market. At an index value of 1000 the value of an S&P 500 futures contract is 250.000$.

[8]) Slippage costs are estimated under the (realistic) assumption that in electronic futures exchanges orders are executed within 10 seconds. An analysis of the S&P 500 futures tick data shows that the mean of the price changes within this interval is 0,02% of contract value. If one assumes that the price moves always unfavorably when profitable trading signals are produced, and that there is an equal chance that the price moves favorably or unfavorably in the case of unprofitable trading signals then one arrives at estimated slippage costs of roughly 0,008%. This

For these reasons the simulation of technical stock futures trading operates under the assumption of overall transaction costs of 0.01% (per trade).[9])

Margins are put at 10% of contract value. This represents an upper limit since the margin requirement in stock index futures markets almost never exceed 10%.

The profitability of any trading system is calculated in the following way. The gross rate of return (per year) is the difference between gross profits (per year) and gross losses (per year). If one subtracts transaction costs one gets the net rate of return.

The gross rate of return (GRR) of any technical trading model can be split into six components, the number of profitable/unprofitable positions (NPP/NPL), the average return per day during profitable/unprofitable positions (DRP/DRL), and the average duration of profitable/unprofitable positions (DPP/DPL). The following relationship holds:[10])

GRR = NPP*DRP*DPP – NPL*DRL*DPL

The riskiness of blindly following a technical trading model is estimated by testing the mean of the single rates of return against zero (only if it is negative does the trading rule produce an overall loss). The t-statistic is a better measure for the return-risk-relationship of technical trading systems than the Sharpe ratio since the latter does not take the number of single returns (open positions) into account, which varies across different models.[11])

3. The performance of technical trading systems based on daily stock prices

3.1 Technical stock trading in the spot market

Table 1 classifies all models according to their performance as measured by the t-statistic into five groups and quantifies the components of profitability for each of them. When trading in the S&P 500 spot market between 1960 and 2000, 11.1% of all models achieve a t-statistic greater than 3 and the average gross rate of return per year over these modes amounts to 9.6%. The t-statistic of 23.6% of all models lies between 1.0 and 3.0, 27.1% generate a t-statistic between 0.0 and 1.0 and 34.8% of all models are unprofitable (t-statistic < 0.0).

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calculation implies that trading signals are unprofitable in 60% of all cases. However, most technical models produce unprofitable signals even more frequently as shall later be documented.

[9]) This assumption is certainly unrealistic as regards trading stock index futures in the more distant past (when electronic exchanges did not exist yet), and it is even more unrealistic as regards trading the stocks comprised by the S&P 500 in the spot market. However, in order to keep the results comparable across markets and time periods the simulations operate with this assumption in all cases.

[10]) When calculating these components all those transactions are neglected which are only caused by switching futures contracts (these transactions are, however, taken into account when calculating the net rate of return).

[11]) If, e. g., two trading rules produce the same ratio between the average of single returns and their standard deviation but a different number of trades, then the return relative to the risk would be greater in the case of that model which trades more frequently. This fact is reflected by the t-statistic but not by the Sharpe ratio. The latter is mostly used to compare the return (in excess of the risk-free rate) and risk of holding different assets over a certain period by calculating, e. g., the mean and standard deviation of daily returns. In this case the number of single returns is the same for the assets under investigation so that the informational content of the t-statistic and the Sharpe ratio would be equivalent. This is so because the t-statistic testing the mean of the single rates of return against zero differs from the Sharpe ratio only by the factor $\sqrt{n-1}$ (where n is the sample size) and by the risk-free rate.

As regards the pattern of profitability the following observations can be made. First, the number of profitable positions is always smaller than the number of unprofitable positions. Second, the average return per day during profitable positions is lower than the average return (loss) during unprofitable positions (the average slope of price movements during the - relatively longer lasting - profitable positions is flatter than during the short lasting unprofitable positions). Third, the average duration of profitable positions is several times greater than that of unprofitable positions. This pattern characterizes technical trading in general (Schulmeister, 1988, 2002, 2007A and 2007B): The profits from the exploitation of relatively few persistent price trends exceed the losses from many but small price fluctuations ("cut losses short and let profits run").

Table 1 shows also the performance of the 2580 trading systems over 4 subperiods since 1960. It turns out that the average gross rate of return has continuously declined in the S&P 500 spot market from 8.6% (1960/71) to 2.0% (1972/82), -0.0% (1983/91) and finally to –5.1% (1992/2000). A similar result is reported by Sullivan-Timmermann-White, 1999, and - for currency markets – by Ohlson (2004) and Schulmeister (2007A).

Table 1: Components of the profitability of 2,580 trading system by subperiods and classes of the t-statistic

S & P 500 spot market, daily data, 1960-2000

	Number of models				Mean for each class of models					
	Absolute	Share in %	Gross rate of return	t-statistic	Profitable positions			Unprofitable positions		
					Number per year	Return per day	Duration in days	Number per year	Return per day	Duration in days
1960-1971	2580	100.0	8.6	2.30	6.8	0.08	44.2	8.7	– 0.12	13.3
1972-1982	2580	100.0	2.0	0.45	6.7	0.10	40.9	11.5	– 0.16	12.8
1983-1991	2580	100.0	– 0.0	– 0.01	6.4	0.11	40.3	12.9	– 0.16	13.5
1992-2000	2580	100.0	– 5.1	– 1.12	6.3	0.09	40.2	14.1	– 0.16	12.8
1960-2000	2580	100.0	1.9	0.84	6.5	0.09	41.9	11.5	– 0.15	13.0
t-statistic										
<0	897	34.8	– 1.3	– 0.57	5.5	0.09	41.3	9.6	– 0.15	14.6
0-<1	786	30.5	1.0	0.43	4.8	0.08	51.4	9.1	– 0.13	15.7
1-<2	393	15.2	3.4	1.46	5.9	0.09	46.1	11.4	– 0.14	12.7
2-<3.0	217	8.4	5.5	2.42	8.4	0.10	31.7	15.0	– 0.16	7.9
>3	287	11.1	9.6	4.33	14.2	0.13	20.1	21.8	– 0.20	4.9

3.2 Technical stock trading in the futures market

The 2580 trading systems are significantly unprofitable on average when trading S&P 500 futures based on daily data between 1983 and 2000, they produce an average rate of return of –5.9% per year (table 2). This performance is even worse than in the S&P 500 spot market over the same period (GRR: -2.5%). The main reason for this difference stems from the strong increase in stock prices between 1983 and 2000. Under this condition technical models hold long positions for a longer time span as compared to short positions. At the same time the return from holding a long position in stock index futures is lower than from holding stocks in the spot market if the rate of interest exceeds the dividend yield (as has been the case).

The pattern of profitability (i.e., the relations between its components) is the same in the S&P 500 futures and spot market. As in the spot market the best performing models are those which specialize on the exploitation of short-term stock price trends (table 1 and 2).

This pattern implies that "underlying" price trends occur also in the stock index futures markets more frequently than could be expected under a random walk. However, this non-randomness cannot be profitably exploited by technical models due to the too frequent "jumps" of daily futures prices causing low ratios between the number of profitable and unprofitable positions as well as between the average return per day during profitable and unprofitable positions.

Table 2: Components of the profitability of 2,580 trading systems by subperiods and classes of the t-statistic

S & P 500 futures market, daily data, 1983-2000

	Number of models				Mean for each class of models					
	Absolute	Share in %	Gross rate of return	t-statistic	Profitable positions			Unprofitable positions		
					Number per year	Return per day	Duration in days	Number per year	Return per day	Duration in days
1983-1991	2,580	100.0	– 5.1	– 0.97	6.4	0.11	39.3	14.0	– 0.17	13.7
1992-2000	2,580	100.0	– 6.7	– 1.59	6.5	0.08	38.6	14.4	– 0.16	13.0
1983-2000	2,580	100.0	– 5.9	– 1.75	6.5	0.09	39.1	14.2	– 0.17	13.2
t-statistic										
<0	2,537	98.3	– 6.0	– 1.78	6.4	0.09	39.2	14.2	– 0.17	13.2
0-<1	42	1.6	0.8	0.24	7.6	0.11	36.2	11.0	– 0.15	15.9
1-<2	1	0.0	3.7	1.02	10.2	0.14	20.2	15.8	– 0.15	10.1

The decline in the profitability of technical trading based on daily data could be explained in two different ways. The "adaptive market hypothesis" (Lo, 2004; Neely-Weller-Ulrich, 2006) holds that asset markets have become gradually more efficient, partly because learning to exploit profit opportunities wipes them out, partly because information technologies steadily improve market efficiency (Ohlson, 2004). The second explanation holds that technical traders have been increasingly using intraday data instead of daily data. This development could have caused intraday price movements to become more persistent and, hence, exploitable by technical models. At the same time price changes on the basis of daily data might have become more erratic. This would then cause technical trading to become less profitable based on daily prices (but not on intraday prices).[12])

[12]) Two observations are in favor of the second hypothesis (table 1). First, the profitability of technical stock trading based on daily data has primarily declined due to a decline in the ratio between the number of profitable and unprofitable positions, namely from 0.78 (1960/71) to 0.45 (1992/2000). This decline can be attributed to increasingly erratic fluctuations of daily stock prices. Second, the average duration of profitable positions of the best performing models (t-statistic > 2) has strongly and steadily declined between 1960/72 and 1992/2000. This indicates that stock price trends have become shorter over the sample period.

4. The performance of technical trading systems based on 30-minutes-futures-prices 1983-2000

4.1 Overview of the performance of 2580 trading systems

Figures 1 and 2 show the distribution of the 2580 models by their gross and net rate of return. When trading S&P 500 futures contracts the models produce an average gross return of 8.8% per year between 1983 and 2000. Due to the high number of transactions when trading is based on 30-minutes-data the net rate of return is significantly lower (4.3%).

Figure 1: Distribution of 2580 trading systems by the gross rate of return 1983-2000
S&P 500 futures market, 30-minutes-data

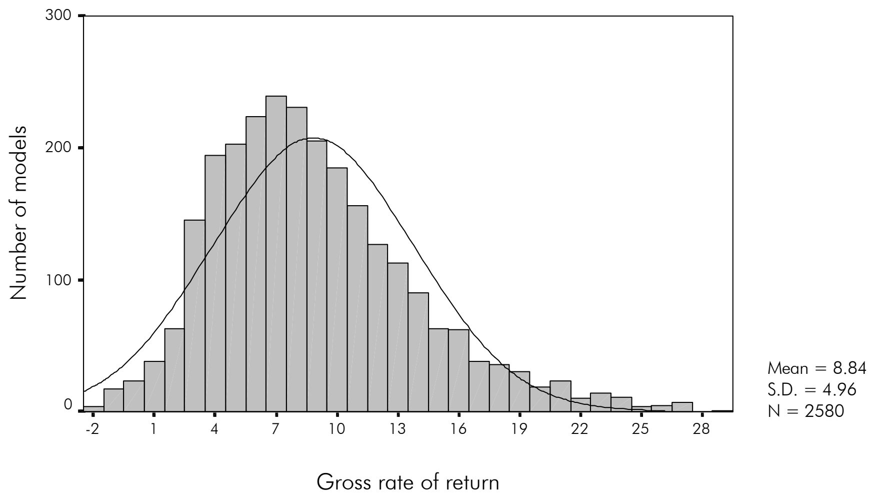


Figure 2: Distribution of 2580 trading systems by the net rate of return 1983-2000
S&P 500 futures market, 30-minutes-data

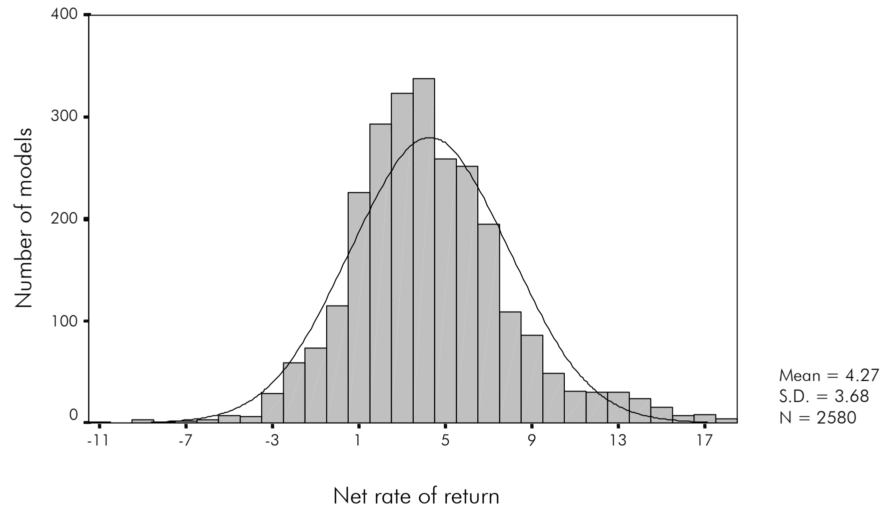
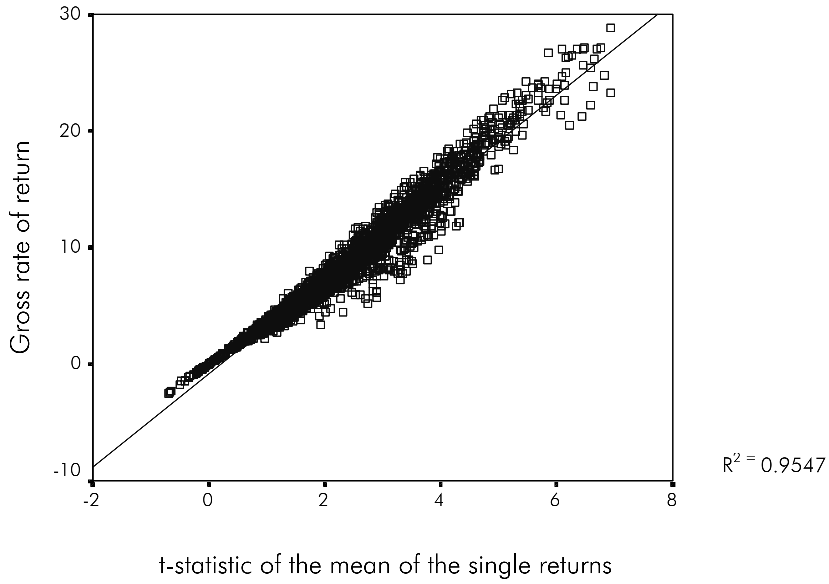


Figure 1 shows that there exist abnormally many highly profitable models among the sample of 2580 models (the distribution is skewed to the right). At the same time the most profitable models trade much more frequently than on average over all models (as shall later be demonstrated). Hence, the distribution of models by the net rate of return (Figure 2) is more symmetric as compared to the distribution by gross returns (Figure 2).

The t-statistic of the mean of the single rates of return exceeds 2.0 in most cases (figure 3), it amounts on average over all models to 2.4 (table 3). This result indicates that there was rather little risk associated with technical stock trading based on 30-minutes-data if traders had rigidly adhered to a particular model out of the sample of 2580 models. However, the riskiness of technical trading rises when traders engage in what can be called "model mining". If a trader searches for the "optimal" system out of a great number of different models on the basis of their past performance, then he might suffer substantial losses out of sample if its abnormal profitability in sample occurred mainly by chance (see section 5).

Figure 3: Profitability and riskiness of 2580 technical trading systems 1983-2000
S&P 500 futures market, 30-minutes-data



The second source of risk of technical stock trading concerns the fact that every technical model produces sequences of (mostly) unprofitable positions which accumulate to substantial losses over the short run. These losses might prevent a trader from sticking to a certain rule over the long run.

4.2 The performance by types of models and trading rules

When trading S&P 500 futures based on 30-minutes-data the RSIN models and the momentum models (GRR: 11.5% and 10.1%, respectively) perform better than the moving average models (GRR: 8.4% - table 3). The contrarian rules SG 4 to SG 6 are significantly more profitable than the trend-following rules SG 1 to SG 3 (GRR: 10.9% and 6.4%, respectively). Due to the frequent transactions involved in trading based on intraday data the net rate of return is by roughly 4 percentage points lower than the gross return. This difference is greater in the case of contrarian trading rules (5.5 percentage points) as compared to trend-following rules (3.5 percentage points) since the former "specialize" on the exploitation of very short-term price runs and, hence, generate more transactions than trend-following systems.

Table 3: Components of the profitability of technical trading by types of models
S & P 500 futures market, 30-minutes-data

Types of models	Share of profitable models in %	Gross rate of return	Net rate of return	t-statistic	Mean and standard deviation for each class of models – Profitable positions: Number per year	Profitable positions: Return per day	Profitable positions: Duration in days	Unprofitable positions: Number per year	Unprofitable positions: Return per day	Unprofitable positions: Duration in days
					In sample 1983-2000					
Moving Average	98.5	8.4	4.5	2.34	74.67	0.39	2.8	117.96	– 0.57	1.1
Momentum	100.0	10.1	2.3	2.61	147.49	0.42	1.8	235.94	– 0.69	0.5
RSIN	99.6	11.5	4.0	3.08	148.28	0.50	1.7	225.68	– 0.66	0.7
SG 1	95.4	7.3	2.6	1.86	80.49	0.32	3.4	152.90	– 0.50	1.1
SG 2	96.4	4.7	2.1	1.35	46.94	0.34	3.7	76.15	– 0.51	1.4
SG 3	100.0	7.3	3.9	2.37	65.28	0.47	2.0	104.64	– 0.73	0.7
SG 4	99.8	12.0	6.5	3.02	111.33	0.39	2.6	156.47	– 0.54	1.2
SG 5	100.0	9.8	4.5	2.83	102.24	0.44	1.9	160.43	– 0.66	0.7
SG 6	100.0	10.8	5.3	2.88	107.97	0.42	2.2	163.83	– 0.58	1.0
All models	98.7	8.8	4.3	2.43	87.61	0.40	2.6	137.90	– 0.59	1.0
					Out of sample 2001-2006					
Moving Average	49.5	0.59	– 3.45	0.10	74.51	0.39	2.73	124.54	– 0.61	1.08
Momentun	68.0	2.1	– 5.82	0.33	147.58	0.43	1.75	242.8	– 0.71	0.55
RSIN	69.3	2.9	– 4.67	0.47	147.24	0.51	1.56	229.95	– 0.67	0.76
SG 1	20.7	– 2.95	– 7.88	– 0.46	80.02	0.32	3.36	162.37	– 0.54	1.07
SG 2	27.3	– 1.90	– 4.49	– 0.32	47.52	0.34	3.65	79.53	– 0.56	1.38
SG 3	52.8	0.85	– 2.75	0.17	67.42	0.49	1.98	110.59	– 0.81	0.71
SG 4	85.5	5.15	– 0.35	0.78	110.31	0.39	2.50	161.20	– 0.56	1.26
SG 5	48.7	0.53	– 4.90	0.10	100.91	0.45	1.83	167.94	– 0.70	0.70
SG 6	72.9	2.78	– 2.85	0.45	107.29	0.42	2.15	171.16	– 0.61	0.94
All models	52.9	0.93	– 3.77	0.15	87.40	0.40	2.54	144.31	– 0.63	1.01

Over the entire period between 1983 and 2000 almost all of the 2580 technical models are profitable, 98.7% of them produce a positive gross rate of return (table 3).[13])

Table 4 classifies all models according to the t-statistic into 5 groups. 28.3% of the models achieve a t-statistic greater than 3.0, their average gross (net) rate of return amounts to 14.9% (7.9%) per year. 32.6% of the models achieve a t-statistic between 2.0 and 3.0. Hence, 60.9% of the trading systems produce a gross rate of return significantly greater than zero over the entire sample period of 18 years. This result can hardly be reconciled with the hypothesis of (weak) efficiency in the S&P 500 futures markets given the great number of different models investigated.

[13]) The original study on which this paper is based was already finished in 2002 (Schulmeister, 2002). In order to take into account the most recent development in stock price dynamics an out-of-sample-test of the performance of the 2580 models between 2001 and 2006 was carried out. The results of this exercise are documented in tables 3, 4, 7 as well as in figure 7. These results will be discussed in section 5.

Table 4: Components of the profitability of 2580 trading systems by subperiods and classes of the t-statisticS & P 500 futures market, 30-minutes-data

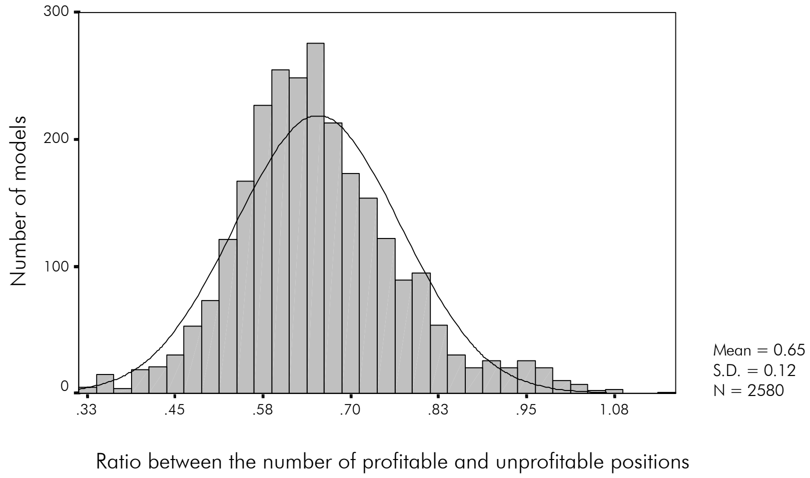
	Relative Share in %	Gross rate of return	Net rate of return	t-statistic	Mean for each class of models Profitable positions Number	Return per day	Duration in days	Unprofitable positions Number	Return per day	Duration in days
					In sample 1983-2000					
1983-1985	100.0	5.1	0.7	0.73	86.2	0.34	2.6	130.3	– 0.49	1.1
1986-1988	100.0	12.1	7.3	0.92	91.4	0.53	2.5	147.9	– 0.78	1.0
1989-1991	100.0	15.4	10.8	1.93	90.4	0.40	2.6	136.7	– 0.56	1.0
1992-1994	100.0	2.1	– 2.1	0.40	79.7	0.26	2.6	128.2	– 0.37	1.2
1995-1997	100.0	6.4	1.9	0.95	87.3	0.34	2.6	136.2	– 0.55	1.0
1998-2000	100.0	12.1	7.2	1.20	92.2	0.50	2.7	150.7	– 0.76	0.9
1983-2000	100.0	8.8	4.3	2.43	87.6	0.40	2.6	137.9	– 0.59	1.0
t-statistic										
<0	1.3	– 0.9	– 3.0	– 0.25	38.2	0.24	5.4	64.8	– 0.37	2.1
0-<1	8.4	2.3	– 0.3	0.67	47.2	0.29	4.2	77.8	– 0.43	1.6
1-<2	29.5	5.2	2.1	1.53	58.7	0.34	3.2	93.5	– 0.50	1.3
2-<3.0	32.6	8.9	4.5	2.51	82.7	0.39	2.4	132.1	– 0.59	0.9
>3	28.3	14.9	7.9	3.93	137.5	0.51	1.5	211.8	– 0.73	0.6
					Out of sample 2001-2006					
2001-2003	100.0	5.44	0.49	0.48	93.53	0.52	2.59	150.72	– 0.82	0.96
2004-2006	100.0	– 2.94	– 7.38	– 0.63	81.41	0.27	2.53	137.67	– 0.43	1.11
2001-2006	100.0	0.93	– 3.77	0.15	87.40	0.40	2.54	144.31	– 0.63	1.01
t-statistic										
<0	47.0	– 3.40	– 6.92	– 0.58	63.23	0.33	3.14	109.87	– 0.56	1.19
0-<1	37.1	2.51	– 2.63	0.42	94.48	0.41	2.28	159.52	– 0.65	0.90
1-<2	11.9	8.34	1.39	1.40	137.56	0.58	1.46	206.75	– 0.78	0.73
2-<3.0	3.5	14.06	6.74	2.32	150.89	0.65	1.17	212.20	– 0.81	0.71
>3	.5	22.93	12.86	3.43	200.65	0.61	1.07	299.87	– 0.75	0.50

4.3 The pattern of profitability of the trading systems

The figures 4, 5 and 6 show how the ratios between the three profitability components of 2580 technical models are distributed. The means of these ratios describe the characteristic profitability pattern of technical trading systems.

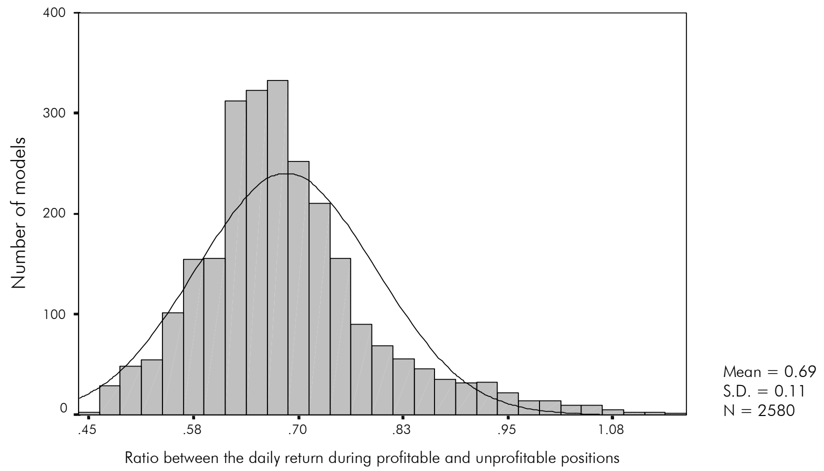
Figure 4: Distribution of 2580 trading systems by the ratio between the number of profitable and unprofitable postitions 1983-2000

S&P 500 futures market, 30-minutes-data



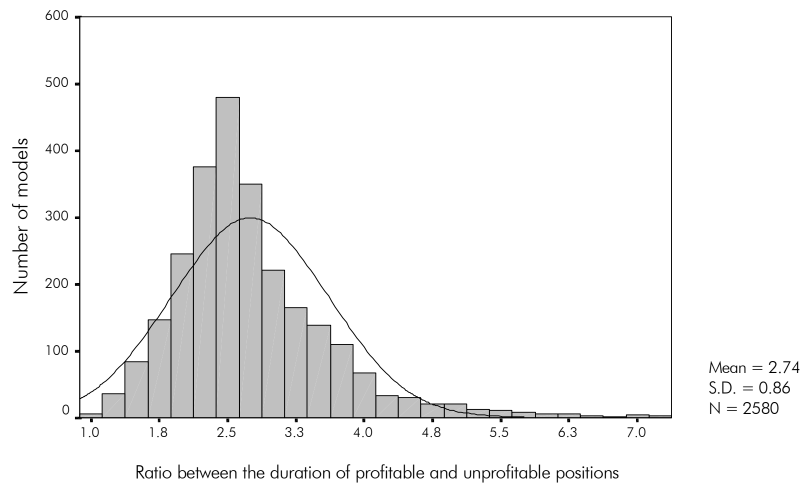
Profitable positions occur on average by 35% less frequently than unprofitable positions. Figure 4 shows that cases where the number of profitable trades exceeds the number of unprofitable trades almost never occur. Also the daily return during profitable positions almost never exceeds the return during unprofitable positions. On average the former is by 31% lower than the latter (figure 5).

Figure 5: Distribution of 2580 trading systems by the ratio between the daily return during profitable and unprofitable positions 1983-2000
S&P 500 futures market, 30-minutes-data



Hence, the high ratio between the average duration of profitable and unprofitable positions (2.74 on average) is the main reason for the profitability of technical stock trading based on 30-minutes-data are used. This ratio reflects the exploitation of persistent stock price movements by technical models.

Figure 6: Distribution of 2580 trading systems by the ratio between the duration of profitable and unprofitable positions 1983-2000
S&P 500 futures market, 30-minutes-data



4.4 Clusters of technical models

In order to detect similarities in the trading behavior of certain groups of technical models, statistical clustering techniques were used. These methods classify all models into different groups (clusters) under the condition that the differences between the models (with respect to the components of the profitability in our case) are minimized within each cluster and maximized across the clusters. The simple approach called K-Means Cluster Analysis was adopted (provided by the SPSS software package). For this approach, the number of clusters has to be predetermined (in our case three clusters are sufficient to illustrate characteristic differences in the trading behavior of technical models).

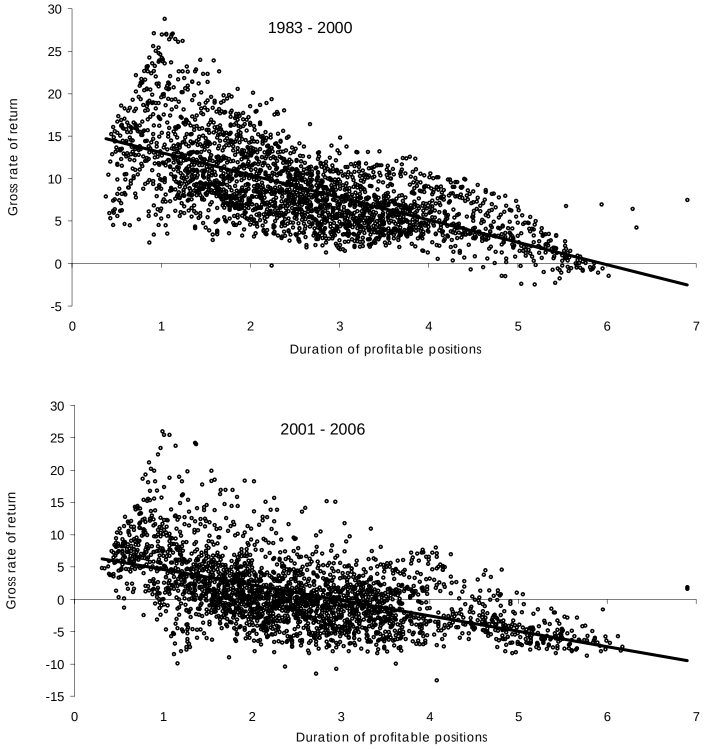
Table 5 shows the results of the cluster analysis. The 151 models of cluster 1 produce the highest number of open positions (649.1 per year on average), mainly for that reason the duration of profitable positions is relatively short (0.8 days on average). Hence, cluster 1 comprises those (fast) models which are most sensitive to price changes. The 631 models of cluster 2 signal 433.3 open positions per year, the profitable positions last 1.7 days on average. Most models belong to cluster 3 which comprises 1798 (slow) models which produce 152.1 open positions per year, their profitable positions last 3.1 days on average.

Table 5: Cluster of 2,580 trading systems according to profit components
S & P 500 futures market, 30-minutes-data, 1983-2000

	Number of models	Gross rate of return	Mean for each class of models					
			Profitable positions			Unprofitable positions		
			Number per year	Return per day	Duration in days	Number per year	Return per day	Duration in days
All models								
Cluster 1	151	17.1	256.0	0.64	0.8	393.1	– 0.90	0.3
Cluster 2	631	12.5	124.7	0.45	1.7	208.6	– 0.70	0.5
Cluster 3	1,798	6.9	60.4	0.36	3.1	91.7	– 0.52	1.2
Total	2,580	8.8	87.6	0.40	2.6	137.9	– 0.59	1.0

The average gross rates of return differ significantly across the three clusters. The fast models of cluster 1 perform by far best. These models produce an average gross rate of return of 17.1%. Also the models of cluster 2 achieve a gross rate of return (12.5%) which is higher than on average over all 2580 models. By contrast, the comparatively slow models of cluster 3 produce an average gross rate of return of only 6.9%.

Figure 7: Duration of profitable positions and the performance of 2,580 trading systems



The results of the cluster analysis are confirmed by figure 7. It shows the relationship between the performance of the models and their "specialization" on the exploitation of stock price trends of various lengths: The shorter is the average duration of the profitable positions of the models the higher is their profitability on average. For this reason the differences in the performance of the models is less pronounced on the basis of the net rate of return as compared to the gross rate (compare figures 1 and 2).

4.5 Performance of all models by subperiods

Table 4 shows how the 2580 technical models perform in the S&P 500 futures market over 6 subperiods between 1983 and 2000. The most important observations are as follows. First, in contrast to trading based on daily data there is no clear trend of a declining profitability when technical stock trading is based on 30-minutes-data. Second, the performance of the 2580 models varies significantly across subperiods. The models produce the highest returns over the subperiods 1989/91, 1986/88 and 1998/2000, whereas they perform comparatively worse between 1983 and 1985 and between 1992 and 1994.

Table 6 compares the performance of those models which are profitable in each of the 6 subperiods ("stable models") to the performance of the other ("unstable") models. Stable models are significantly more profitable than unstable models, the former produce a gross (net) rate of return of 12.7% (6.6%) on average; the latter achieve only 6.2% (2.7%). At the same time, stable models trade comparatively often (fast models), hence, the difference between gross and net returns is larger in the case of stable models as compared to unstable models.

Table 6: Frequency and performance of stable and unstable trading models
S & P 500 futures market, 30-minutes-data, 1983-2000

Types of models	Share of stable models in %[1])	Stable models[1])			Unstable models[1])		
		Gross rate of return	Net rate of return	t-statistic	Gross rate of return	Net rate of return	t-statistic
		Mean over each class of models					
Moving average	37.8	12.5	7.2	3.40	5.9	2.9	1.70
Momentum models	48.2	13.0	4.1	3.31	7.4	0.7	1.95
Relative strength models	51.8	14.2	5.3	3.83	8.7	2.6	2.28
SG 1	18.1	14.0	6.2	3.36	5.8	1.8	1.53
SG 2	9.4	10.2	6.1	2.80	4.1	1.7	1.20
SG 3	50.8	9.3	5.3	2.96	5.3	2.5	1.75
SG 4	47.4	14.9	8.2	3.70	9.3	5.0	2.41
SG 5	54.7	12.5	6.1	3.55	6.5	2.6	1.96
SG 6	52.6	13.8	7.1	3.61	7.5	3.3	2.08
All models	40.0	12.7	6.6	3.44	6.2	2.7	1.76

[1]) Stable models are profitable (GRR > 0) in each of the 6 subperiods, all others are unstable.

4.6 Performance of the 25 best models ex post and ex ante

Almost all of 2580 trading models produce excessive returns over the entire sample period, 40% of these models are profitable over each subperiod, and the profitability of the models is exclusively due to the exploitation of stock price trends of varying lengths. Hence, it is implausible that the ex-post performance of stock futures trading based on 30-minute-data is the result of data snooping. However, the "trending" of stock prices does not ensure the profitability of technical trading ex ante. This is so for the following reason.

The ex-post profitability of the best models consists of two components. The first stems from the "normal" non-randomness of stock price dynamics, namely, the occurrence of trends. The second component stems from the selection bias since a part of the ex-post profits of the best models would have been produced only by chance (this bias increases as more models are tested and as the test period is shortened). Now, if the profitability of an "optimal" model is mainly the result of this "model mining" then the model will perform much worse over the subsequent period. However, if the ex-post-profitability stems mainly from the exploitation of "normal" price trends then it might be reproduced ex ante.

In order to investigate this matter, the following exercise is carried out. In a first step the 25 best models are identified on the basis of their ex-post performance as measured by the net rate of return. Then the performance of the selected models is simulated over the subsequent subperiod. The main results are as follows (table 7):

- The ex-post-performance of the 25 best models is much better than the average performance of all models. E. g., the best models produce an average gross rate of return over the six subperiods between 1983 and 2000 of 30.4% (all models: 8.8%).
- The ex-ante-profitability of the best models is significantly better than the average over all models. The best models achieved ex ante an average gross rate of return of 18.7%

between 1986 and 2000, over the same period the gross rate of return of all models amounts to only 9.6% (table 8).

- Almost all best models produce positive ex-ante-returns over each subperiod, in only 3 out of 125 cases do single models produce net losses.

Table 7: Performance of the 25 most profitable trading systems by subperiods and types of models
In sample and out of sample
S & P 500 futures market, 30-minutes-data

	Gross rate of return	t-statistic	Net rate of return	Duration of profitable positions	Gross rate of return	t-statistic	Net rate of return	Duration of profitable positions
	Ex post				Ex ante			
1983-1985	35.2	4.51	28.62	1.4				
1986-1988	41.6	2.80	35.16	1.7	28.8	1.72	21.3	1.4
1989-1991	35.7	4.14	27.71	1.4	27.1	3.15	20.7	1.7
1992-1994	18.3	3.31	14.02	2.4	15.1	2.79	8.5	1.5
1995-1997	25.6	3.33	17.27	1.6	7.8	1.00	1.7	1.7
1998-2000	26.0	2.39	21.82	3.3	14.6	1.30	5.9	1.6
2001-2003	35.4	2.88	26.92	1.1	2.2	0.19	-2.1	3.3
2004-2006	11.5	2.06	8.23	2.8	2.8	0.46	-4.0	1.2

Table 8 summarizes the means over the rates of return and over the three ratios of the profitability components of all models as well as of the 25 best models expost (in sample) and ex ante (out of sample). In addition, t-statistics test for the significance of the difference between the means of the best models and the means of all models.

The mean of the ratio between the number of profitable and unprofitable positions as well as the mean of the ratio between the daily return during profitable and unprofitable positions are significantly higher in the case of the 25 best models in sample than in the case of all models. By contrast, the mean ratio between the duration of profitable and unprofitable positions is lower in the case of the (ex post) best models as compared to the average over all models. This pattern is typical for the best performing models in general, and not just for the 25 best performing models. Table 4 shows that the profitability structure of the 731 models which produce a t-statistic greater than 3 is similar though less pronounced than in the case of the 25 best models. The mean gross rate of return of the best models (29.4%) is roughly three times as high as the mean over all models (9.6%).

Table 8: Distribution of trading systems by the rate of return and the ratio of profit components over five subperiods
S & P 500 futures market, 30-minutes-data, 1986-2000

	Mean	t-statistic
	All models (N = 12900)	
Gross rate of return	9.6	
Net rate of return	5.0	
NPP/NPL	0.65	
DRP/DRL	0.68	
DPP/DPL	2.80	
	The 25 most profitable models ex post (N = 125)	
Gross rate of return	29.4	24.9
Net rate of return	23.2	25.6
NPP/NPL	0.78	7.6
DRP/DRL	0.81	9.1
DPP/DPL	2.51	– 3.3
	The 25 most profitable models ex ante (N = 125)	
Gross rate of return	18.7	9.7
Net rate of return	11.6	7.3
NPP/NPL	0.78	9.1
DRP/DRL	0.81	11.1
DPP/DPL	2.13	– 9.1

NPP (NPL) . . . Number of profitable (unprofitable) positions per year.
DRP (DRL) . . . Return per day during profitable (unprofitable) positions.
DPP (DPL) . . . Average duration of profitable (unprofitable) positions.

The t-statistic tests for the significance of the difference between the mean of the four variables over the 125 cases of the best models (in and out of sample) and the respective mean over the 12900 cases of all models.

The pattern of the ex-ante- profitability of the 25 best models is roughly the same as in sample (table 8). Consequently, the 25 best models produce also ex ante a gross return (18.7%) which is significantly higher than the mean return over all models (9.6%). Hence, when trading S&P 500 futures based on 30-minutes-data that pattern which is typical for the 25 best models in sample could be reproduced out of sample.

5. The out-of-sample-performance of 2580 trading systems 2001-2006

An out-of-sample-test reveals that the 2580 technical models based on 30-minutes-data would have performed much worse between 2001 and 2006 as compared to the sample period 1983-2000. The main out-of-sample-results can be summarized as follows:

- The average gross rate of return amounts to only 0.9% per year, net of transaction costs the models would have made an average loss of 3.8% per year (table 3).
- The profitability of the models has been declining over the out-of-sample-period. The average gross rate of return fell from 5.4% between 2001 and 2003 to -2.9% between 2004 and 2006 (table 4).

- The moving average models would have performed worse than the momentum models and the RSI models (the respective gross rates of return are 0.6%, 2.1%, and 2.9%, respectively – table 3).
- Contrarian models produced better results than trend-following models. The trading rule SG4 (GRR: 5.2%) outperformed the other types of signal generation (table 3).
- The 25 models which performed best over the most recent subperiod would no longer have been more profitable than the average of all models (table 7).
- The pattern of profitability has remained roughly the same as between 1983 and 2000 (however, the data points in figure 7 shifted downwards).

These results could be explained in two different ways. According to the "adaptive market hypothesis" (Lo, 2004; Neely-Weller-Ulrich, 2006) asset markets become more efficient though only gradually. The second explanation holds that the increasing "speed" of trading causes asset price trends to become more pronounced at higher data frequencies. This hypothesis implies that the profitability of technical trading systems has moved from 30-minutes date to higher frequency data over the most recent years (in a similar fashion the profitability of technical trading had shifted from daily to 30-minutes-prices over the 1980s).

The "adaptive market hypothesis" assumes that an increasing number of traders will exploit profit opportunities provided by, e. g., intraday price trends, and by doing so will wipe out these opportunities. However, this assumption does not hold for technical traders since an increasing use of technical systems actually strengthens asset price trends (for an analysis of this feed-back see Schulmeister, 2006 and 2007C). If, e. g., technical traders increasingly base their models on 5-minutes-prices instead of 30-minutes-prices then price movements become more trending at the 5-minutes-frequency and less trending at the 30-minutes-frequency.

Two observations support the hypothesis that technical trading and its profitability might have moved from 30-minutes-data to higher data frequencies:

- Trading volume in stock futures has continued to increase at a very high speed. According to the Bank of International Settlements (BIS) stock futures trading (notional values) in North America rose by 17.1% per year between 2000 and 2006 to 32,867 bill. $ (www.bis.org/publ/qtrpdf/r_qa0703.pdf#page=108). A great deal of these transactions might have been triggered by technical trading systems based on intraday data (the number of surprising news has most probably not kept up with transactions).
- Survey studies as well as anecdotical evidence suggest that the popularity of technical analysis has further increased among professional and amateur traders. For recent survey studies see Gehrig-Menkhoff, 2006, and Menkhoff-Taylor, 2007. In addition to the results of surveys among (professional) traders, two developments point at the rising importance of "high-speed technical trading". First, the use of "automated trading systems" has become increasingly popular, and, second, a rising number of amateurs engage in "day trading".[14])

[14]) When searching Google for „automated trading systems" and „technical day trading" one gets 1,48 Mill. and 9,6 Mill. hits, respectively (on March 20, 2007).

Hence, technical trading of stock index futures has most probably not lost its popularity in recent years. At the same time technical traders use increasingly price data of higher frequencies than 30-minutes-data (this is true for "automated systems" as well as for "day trading" – see Velez-Capra, 2000). Given the interaction between the aggregate behavior of technical trading systems and the "trending" of asset prices (Schulmeister, 2006 and 2007C) it seems plausible that persistent movements in stock index futures prices have become shorter and, hence, exploitable only on the basis of data frequencies higher than 30-minutes-prices. The fact that the trading rule SG 4 would have performed better between 2001 and 2006 than all other rules tested in this study is in line with this presumption (table 3 – SG 4 gets on and off a trend faster than the other rules).

6. Summary and evaluation of the results

The main results of the study can be summarized as follows:

- Technical trading in the S&P 500 spot market based on daily prices would not have been markedly profitable between 1960 and 2000. The 2580 models tested would have produced an average gross rate of return of only 1.9% per year.
- The profitability of technical trading in the S&P 500 spot market has declined over time from 8.6% per year (1960/71) to 2.0% (1972/82), -0.0% (1983/91) and finally to –5.1% (1992/2000).
- The 2580 models are even more unprofitable when trading S&P 500 futures contracts between 1983 and 2000.
- The picture is very different for stock futures trading based on 30-minutes-data. The 2580 models produce an average gross return of 8.8% per year between 1983 and 2000. Due to the high number of transactions the net rate of return is significantly lower (4.3%).
- Contrarian models achieve a significantly higher gross rate of return (10.9%) than trend-following models (6.4%).
- With a margin requirement of 10%, the 2580 technical models would have produced a net rate of return per capital invested of 43% per year between 1983 and 2000.
- The probability of making an overall loss when strictly following most of these models was close to zero.
- The profitability of technical stock futures trading is exclusively due to the exploitation of persistent price trends around which stock prices fluctuate.
- These results do not change substantially when technical stock index futures trading is simulated over 6 subperiods between 1983 and 2000. In only 2499 out of 15480 cases did the technical models produce losses.
- Those 25 models which performed best over the most recent subperiod produce a significantly higher gross return ex ante (i. e., over the subsequent subperiod) than all models (18.7% and 9.6%, respectively).
- Over the out-of-sample-period 2001-2006 the 2580 trading systems (based on 30-minutes-data) would have performed much worse than between 1983 and 2000. This result might

be due to a further increase in the “speed” of trading which in turn might have caused persistent stock price movements to become exploitable only on the basis of data frequencies higher than 30-minutes-prices.

The main reason why the profitability of technical stock trading has been moving during the 1980s from trading based on daily data to trading based on intraday data might stem from the feed-back between the use of technical analysis and asset price dynamics. Computer software for testing and applying technical models as well as the internet facilitated the use of intraday data. As a consequence intraday price movements have become more persistent and, hence, exploitable by higher-frequency technical models (for the impact of the aggregate trading behavior of technical models upon asset price dynamics see Schulmeister, 2006 and 2007C). At the same time price changes on the basis of daily data have become more erratic.

The results of this study do not imply that technical models represent "money machines” which can easily be run. This is so because technical stock trading – in particular when based on high frequency data - involves different risks which are greater for amateurs as compared to professional traders:

- Due to the frequent occurrence of "whipsaws,” technical models often produce sequences of mostly unprofitable trades which accumulate to substantial losses. These losses are particularly high if stock futures are traded (leverage effect).
- Lack of financial resources might also prevent amateur technical traders from sticking to the selected model during "whipsaws” (switching models can easily increase the overall loss).
- "Model mining” represents a particularly important source of risk. If a technical trader searches for the "optimal” model out of a great variety of trading systems on the basis of their performance in the (most recent) past, then the selected model might suffer substantial losses out of sample if its abnormally high profitability in sample occurred mainly by chance.
- Over the past 20 years persistent stock price runs have occurred on the basis of 30-minutes-data but not on the basis of daily data. This development makes it difficult to successfully use technical systems for those amateur traders ("dentists and doctors”) who practice trading only in the evening.

Despite these caveats, one can conclude from the results of this study that professional technical traders are most likely able to earn abnormal returns in the S&P 500 stock index futures market. A disciplined use of technical models should therefore be considered rational, in contrast to rational expectations and behavioral finance theories. Hence, I would finally like to sketch how technical trading could be viewed as rational behavior (this is, in many respects, the world as perceived by the "imperfect knowledge economics" approach of Frydman-Goldberg, 2007; an early sketch can be found in Schulmeister, 1987):

- There are three types of traders in the market. Fundamentalists, who base their expectations primarily on economic news, technical traders, who rely on the most recent price movements, and bandwagonists, who respond to "market moods” and the related price trends.

- The beliefs of traders concerning the functioning of the economy are heterogeneous. Hence, traders use different models and process information in different ways. This holds true also within each group of traders.
- Price movements are the aggregate outcomes of the transactions of all traders.
- As a consequence, traders have to form expectations about expectations of all other traders (Keynes' "beauty contest" problem).
- This problem cannot be solved quantitatively due to the lack of perfect knowledge. To put it concretely: One cannot quantify to which level a price will move in reaction to a certain piece of news (even if "technicians" and bandwagonists would not exist).
- Consequently, actors form their expectation on which they finally base their trading decision in terms of the direction of the imminent price movement.

Technical analysis fits this type of expectations formation particularly well since it also involves only directional expectations. However, technical trading does not even imply that the single trading signals correctly forecast the direction of subsequent price movements in most cases (trading signals are more often wrong than they are right as traders know). Moreover, if a trend develops, no technical model forecasts how long it will last and to which price level it might lead. Hence, the only "forecast" implied by the use of technical models concerns the pattern in asset price movements as a whole, i. e., the sequence of upward and downward trends interrupted by "whipsaws".

On the one hand, technical trading systems exploit price trends in asset markets, on the other, the use of these trading systems strengthen and lengthen these trends (Schulmeister, 2006 and 2007C). This interaction might have contributed to a gradual change in the system of asset price determination:

- The profitability of technical trading causes more and more market participants to base their activity on this strategy. The related increase in the volume of transactions is fostered by the diffusion of new information and communication technologies.
- These technologies enable traders to apply technical models on intraday data frequencies which further increases the speed of transactions. As a consequence, the persistence of price trends on the basis of intraday data rises, feeding back upon the profitability of "fast" technical models.

Under these conditions, it becomes progressively more difficult to form expectations about the fundamental price equilibrium and, hence, to speculate rationally. The results of this study fit well into this hypothetical picture. They suggest that technical stock trading on the basis of intraday data can be considered a profitable and, hence, rational adaptation to inherently unstable asset markets.

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