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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. When based on daily data, the profitability of 2580 technical models has steadily declined since 1960, and has been unprofitable since .the early 1990s. However, when based on 30-minutes-data the same models produce an average gross return of 7.2% per year between 1983 and 2007. These results do not change substantially when trading is tested over eight subperiods. In particular, there is no clear trend of a declining profitability of technical stock trading based on 30-minutes-data. Those 25 models which performed best over the most recent subperiod produce a significantly higher gross return over the subsequent subperiod than all models. Between 2001 and 2007 the 2580 models perform worse than over the 1980s and 1990s. This result could be due to stock markets becoming recently 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 rules that are most probably not used in practice, at least not systematically. 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.

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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 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 (see the "Adaptive Market Hypothesis" of Lo, 2004, as example of an alternative approach). 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 (Neely–Weller–Ulrich, 2007; Olson, 2004; Schulmeister, 2008A and 2008B) 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 (this issue is investigated by Sullivan – Timmermann - White, 1999, and by Neely – Weller – Ulrich, 2007).

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 (1960/2007) and in the stock index futures market (1983/2007). These models comprise trend-following as well as contrarian trading systems. My analysis is based on daily and 30-minute data. 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 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), –5.1% (1992/2000) to -0.8% (2001/07).

[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 (2006), Okunev-White (2003), Neely-Weller (2006), Schulmeister (2008A and 2008B). Excellent surveys of studies on technical analysis are Park-Irwin (2004) for all asset markets and Menkhoff-Taylor (2007) for the foreign exchange market.

- The picture is very different for stock futures trading based on 30-minutes-data. The 2580 models produce an average gross return of 7.2% per year between 1983 and 2000. The contrarian models perform much better (9.1%) than the trend-following models (4.8%).

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.
- Those 25 models which performed best over the most recent subperiod (in sample = ex post) produce a significantly higher gross return over the subsequent subperiod (out of sample = ex ante) than all models in sample (14.5% and 7.5%, respectively).

Over the last subperiod 2004-2007 (based on 30-minutes-data) the 2580 models performed much worse than between 1983 and 2003. This result could be due to stock markets becoming more efficient recently 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 profitably exploit the (purportedly) frequent occurrence of asset price trends ("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).[2]) 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.[3])

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[2]) 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).

[3]) 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.

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.

## 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 (if one uses 30-minutes-data, then MAL would lie between 10 and 30 intervals of 30 minutes).

The basic trading rule of average models is as follows (signal generation 1/SG1):

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:

$$MAO(j,k)_t = [(MAS_{j,t}-MAL_{k,t})/MAL_{k,t}]*100 \qquad (1)$$

This type of representation facilitates a (graphical) comparison of the signal generation between moving average models and momentum models. Another way to express the basic trading rule (SG1) is then: Hold a long position when MAO is positive, hold a short position when MAO is negative.

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

$$M(i)_t = [(P_t - P_{t-i})/ P_{t-i}]*100 \qquad (2)$$

The basic trading rule of momentum models is as follows (signal generation 1/SG1):

Buy (go long) when the momentum M(i) turns from negative into positive and sell (go short) in the opposite case. Or equivalently: Hold a long position when M is positive, hold a short position when M is negative.

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 $MAO(j,k)_t$ and $M(i)_t$, respectively, are positive (negative) only if an upward (downward) price movement has persisted for some days (or some 30-minutes-intervals). When and how often $MAO(j,k)_t$ and $M(i)_t$, respectively, cross the zero line depends not only on the persistence of the most recent prices movements but also 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. Figure 1 clarifies 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.

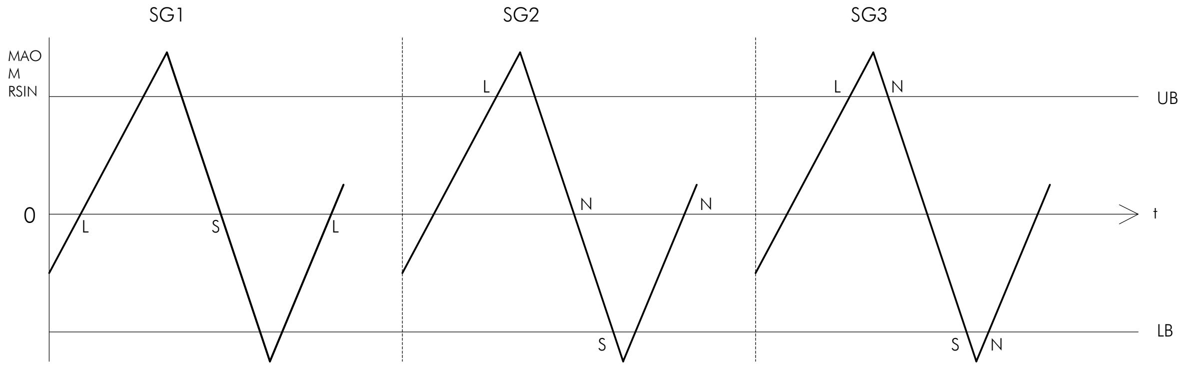
Rule SG 3 differs from SG 2 insofar as the former switches from an open to a neutral position earlier. Whenever the oscillator crosses the upper (lower) band from above (below) rule SG 3 turns from long (short) to neutral. A momentum oscillator, e. g., closes a long position even if the current price 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. Figure 1 shows the differences between the 3 contrarian trading rules.

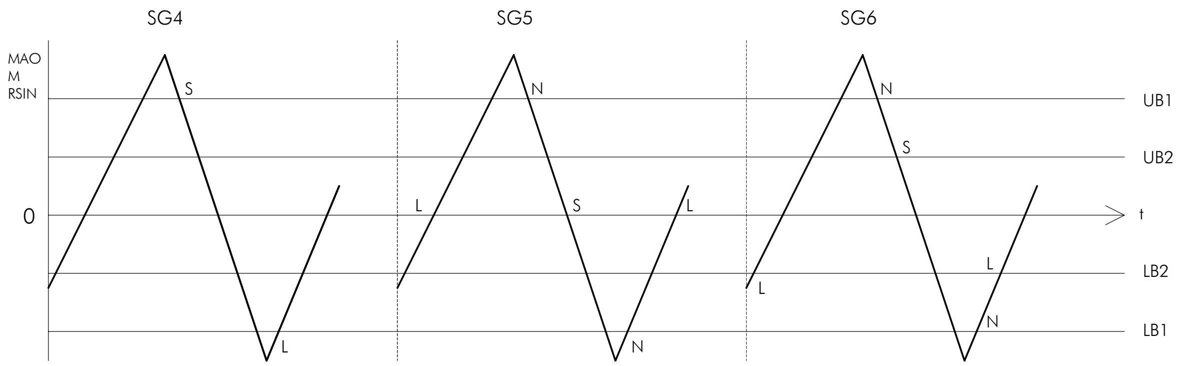
Rule SG 4 is always either long or short (as is the trend-following rule SG 1). According to SG 4 a trader switches from a long (short) to a short (long) position once the oscillator crosses the upper (lower) bound from above (below). Hence, even if the rate of price change in the case of a momentum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

*Figure 1: Signal generation of technical trading systems*

*Trend-following systems*




*Contrarian Systems*




| | |
|---|---|
| SG | Signal generation |
| L | Open a long position (buy) |
| S | Open a short position (sell) |
| N | Go neutral (close the long position = sell; close the short position = buy) |
| MAO | Moving average oscillator |
| M | Momentum oscillator |
| RSIN | Relative strength oscillator (normalized) |
| UB | Upper bound |
| LB | Lower 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).

$RSI(n)_t = 100 – \{100/[1+Up_t(n)/Down_t(n)]\}$ (3)

Where

$Up_t(n)$, $Down_t(n)$ are the average positive or negative price changes within the interval of n days (or of n 30-minutes-periods).

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

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

And

$D_i$ is the daily (30-minutes) price change:

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

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).[4])

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:

$RSIN(n)_t = (1/100)*[RSI(n)_t – 50]*2$ (4)

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.

I shall now describe which models are selected and how their profitability is calculated.

[4]) 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).

### 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 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 (= 6*354). 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).

An 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 an additional 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 (228 = 2*3*38) is the same as the number of momentum models (228 = 6*38). 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 simulated 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 price 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.[5]) 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).

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[5]) When testing 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 2001/2007.

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%.[6]) Slippage costs are put at 0.008%.[7])

For these reasons the simulation of technical stock futures trading operates under the assumption of overall transaction costs of 0.01% (per trade).[8])

The profitability of the trading systems is calculated in the following way. The single rate of return ($SRR_i$) from any position i opened at time t and closed at t+n is

$SRR_i = \{(P_{t+n} – P_t)/P_t\} * 100$ for long positions ($P_{t+n}$ is the sell price)

$SRR_i = \{(P_t – P_{t+n})/ P_t\} * 100$ for short positions ($P_t$ is the sell price)

The single rates of return can be considered as absolute returns in cents If one assumes that there is always 1$ in the game (value of any open position). The sum of all positive (negative) returns gives the gross profits (losses). The gross rate of return (per year) is then 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 number of transactions is always twice the number of open positions and, hence, of the single returns).

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:[9])

GRR = NPP*DRP*DPP – NPL*DRL*DPL

[6]) 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$.

[7]) Slippage costs are incurred if the price moves unfavorably between signal generation and trade execution. These 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. I assume that the price moves always unfavorably when profitable trading signals are produced (40% of all trades), and that there is an equal chance that the price moves favorably or unfavorably in the case of unprofitable trading signals (hence, it is assumed that in 60% of all trades no slippage costs occur). Under these assumptions one arrives at estimated slippage costs of roughly 0,008% (0.02*0.4).

[8]) 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 calculations operate with this assumption in all cases.

[9]) 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). E. g., if a daily model opens a long position on June 2 (and, hence in the June contract), switches to the September contract on June 10, and closes the position on June 22, then DPP is calculated as 20 days.

The probability of making an overall loss when 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).[10])

In the next two sections I report how the 2580 models would have performed in the S&P 500 market, first based on daily data and then based on 30 minutes-data.

## 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 2007, 8.6% of all models achieve a t-statistic greater than 3 and the average gross rate of return per year over these models amounts to 8.3%. The t-statistic of 25.8% of all models lies between 1.0 and 3.0, 31.1% generate a t-statistic between 0.0 and 1.0 and 34.4% of all models are unprofitable (t-statistic < 0.0).

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, 2008A and 2008B): The profits from the exploitation of relatively few persistent price trends exceed the losses from many small price fluctuations ("cut losses short and let profits run").

Table 1 shows also the performance of the 2580 trading systems over 5 subperiods since 1960. It turns out that the average gross rate of return has almost 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) and -0.8% (2001/07), respectively. A similar result is reported by Sullivan-

[10]) The t-statistic of the means of the single returns measures their statistical significance and, hence, estimates the probability of making an overall loss when following a specific trading rule. The t-statistic is therefore conceptually different from the Sharpe ratio which measures the univariate risk-return relation. As the number of observations goes to infinity, an estimated t-statistic will go to zero or to positive or negative infinity. By contrast, an estimated Sharpe ratio will converge to the true Sharpe ratio (I owe this clarification to one referee). However, in the context of the present study (with finite samples) the informational content of the t-statistic and the Sharpe ratio is equivalent. This is so because the t-statistic differs from the Sharpe ratio only by the factor $\sqrt{n-1}$ (where n is the sample size) and by the risk-free rate.

Timmermann-White, 1999, and - for currency markets – by Olson (2004), Neely–Weller–Ulrich (2007) and Schulmeister (2008A, 2008B).

*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, 1960-2007*

| | Number of models | | Gross | t-statistic | Mean for each class of models | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Profitable positions | | | Unprofitable positions | | |
| | Absolute | Share in % | rate of return | | 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 |
| *2001-2007* | 2580 | 100.0 | -0.8 | -0.15 | 6.4 | 0.09 | 43.3 | 12.6 | -0.15 | 13.5 |
| *1960-2007* | 2580 | 100.0 | 1.5 | 0.74 | 6.5 | 0.09 | 42.1 | 11.7 | -0.15 | 13.1 |
| *t-statistic* | | | | | | | | | | |
| <0 | 888 | 34.4 | -1.2 | -0.61 | 5.7 | 0.09 | 40.1 | 10.1 | -0.15 | 14.2 |
| 0-<1 | 803 | 31.1 | 0.9 | 0.46 | 4.7 | 0.08 | 51.9 | 8.8 | -0.13 | 16.1 |
| 1-<2 | 449 | 17.4 | 3.1 | 1.47 | 6.1 | 0.09 | 45.6 | 11.7 | -0.14 | 12.6 |
| 2-<3.0 | 217 | 8.4 | 5.0 | 2.43 | 9.5 | 0.11 | 28.9 | 16.4 | -0.17 | 7.2 |
| >3 | 223 | 8.6 | 8.3 | 4.07 | 14.2 | 0.13 | 21.2 | 23.4 | -0.20 | 4.7 |

## 3.2 Technical stock trading in the futures market

The 2580 trading systems are also unprofitable on average when trading S&P 500 futures based on daily data between 1983 and 2007, they produce an average rate of return of –3.7% per year (table 2). This performance is worse than in the S&P 500 spot market over the same period (GRR: -2.1%). This difference is mainly due to 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 (tables 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 | | Gross rate of return | t-statistic | Mean for each class of models | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Profitable positions | | | Unprofitable positions | | |
| | Absolute | Share in % | | | Number per year | Return per day | Duration in days | Number per year | Return per day | Duration in days |
| *1983-1991* | 2580 | 100.0 | -5.1 | -0.97 | 6.4 | 0.11 | 39.3 | 14.0 | -0.17 | 13.7 |
| *1992-2000* | 2580 | 100.0 | -6.7 | -1.59 | 6.5 | 0.08 | 38.6 | 14.4 | -0.16 | 13.0 |
| *2001-2007* | 2580 | 100.0 | 1.6 | 0.32 | 6.6 | 0.09 | 43.7 | 11.9 | -0.14 | 13.5 |
| *1983-2007* | 2580 | 100.0 | -3.7 | -1.34 | 6.5 | 0.09 | 40.5 | 13.5 | -0.16 | 13.3 |
| t-statistic | | | | | | | | | | |
| <0 | 2361 | 91.5 | -4.1 | -1.48 | 6.6 | 0.09 | 39.2 | 14.1 | -0.16 | 12.6 |
| 0-<1 | 217 | 8.4 | 0.6 | 0.21 | 4.7 | 0.08 | 53.8 | 7.4 | -0.12 | 20.6 |
| 1-<2 | 2 | 0.1 | 2.8 | 1.04 | 5.2 | 0.09 | 40.1 | 7.1 | -0.12 | 17.3 |

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) 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 (Olson, 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).[11]) The next (and main) part of this paper shall shed some light on this issue by investigating the performance of technical stock trading based on intraday data.

## 4. The performance of technical trading systems based on 30-minutes-futures-prices 1983-2007

In this section I document the performance of the same 2580 models in the S&P 500 futures market based on 30-minutes-data instead of daily data. Hence, the data base consists of the prices of the nearby contract which are realized first after the beginning of any 30-minutes interval during trading time (e. g., the price at 9:00:10; 9:30:05; 10:00:15; 10:30:03; etc.).[12]) After

[11]) 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 of the number of profitable positions to the number of unprofitable positions, namely from 0.78 (1960/71) to 0.51 (1992/2007). 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 1992/2007. This indicates that stock price trends have become shorter over the sample period.

[12]) Standard software for technical trading provides the user with the option to select the width of the preferred interval, usually ranging from 1 minute to 1 hour.

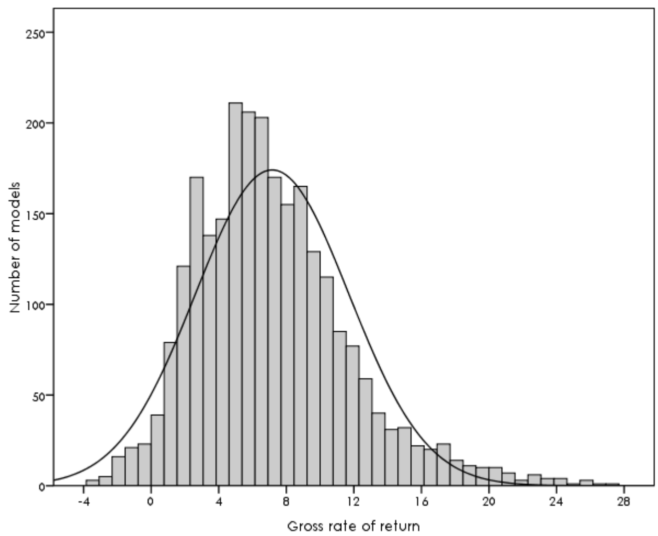
an overview of the performance of all models in terms of gross and net returns, I shall discuss the performance of the 2580 models by type of model and trading rule as well as the pattern of their profitability. Then I classify the models into three groups with comparatively similar trading pattern; the first "specializes" on short-term trends of 30-minutes-prices, the second on medium-term trends and the third on long-term trends. Finally, I document the performance of the models by subperiods and the profitability of the best models in sample and out of sample.

### 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 7.2% per year between 1983 and 2007. Due to the high number of transactions when trading is based on 30-minutes-data the net rate of return is significantly lower (2.6%).

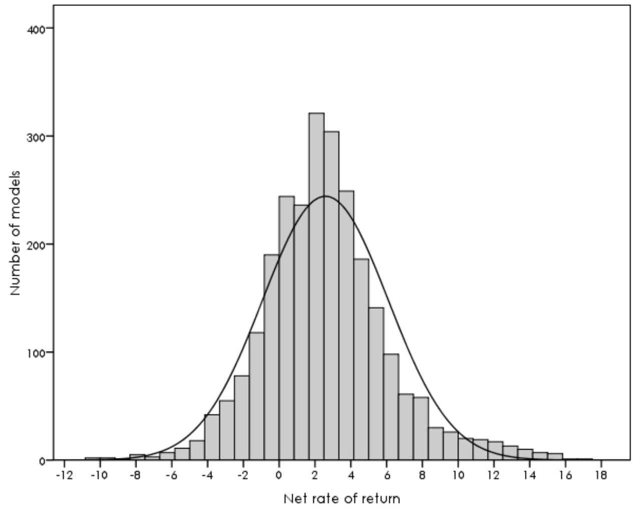
Figure 2 shows that there exist abnormally many highly profitable models among the sample of 2580 models (the distribution is skewed to the right). At the same time the most profitable models trade much more frequently than on average over all models (table 4). Hence, the distribution of models by the net rate of return (i. e., net of transaction costs - figure 3) is more symmetric as compared to the distribution by gross returns (figure 2).

*Figure 2: Distribution of 2580 trading systems by the gross rate of return 1983-2007*
*S&P 500 futures market, 30-minutes-data*




Mean = 7.16
S.D. = 4.547
N = 2,580

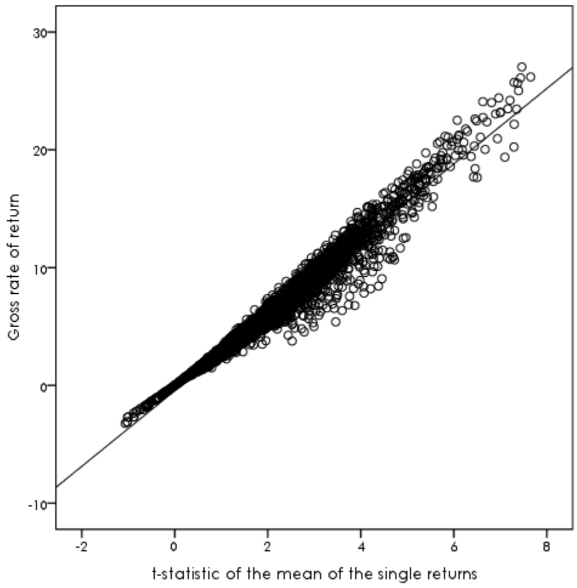
*Figure 3: Distribution of 2580 trading systems by the net rate of return 1983-2007*
*S&P 500 futures market, 30-minutes-data*




Mean = 2.58
S.D. = 3.512
N = 2,580

The t-statistic of the mean of the single rates of return exceeds 2.0 in most cases (figure 4), it amounts on average over all models to 3.7 (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 4: Profitability and riskiness of 2580 technical trading systems 1983-2007*
*S&P 500 futures market, 30-minutes-data*




R2 = 0.96

The close positive correlation between the gross rate of returns of the models and the t-statistic of the means of their single returns implies that the return-risk-relation (risk in the sense of the probability of making an overall loss) rises with the overall profitability of the models (figure 4).

The second source of risk of technical stock trading concerns the fact that every technical model produces sequences of (mostly) unprofitable positions which accumulate substantial losses over the short run. These losses might prevent a trader from sticking to a certain rule over the long run (the occurrence of "whipsaws" - price oscillations around a more or less constant level - is the most important single reason for why technical models produce nearly always substantially more single losses than single profits - see tables 1 to 3 and figure 5).

## 4.2 The performance by types of models and trading rules

When trading S&P 500 futures based on 30-minutes-data, the momentum models and the RSIN models (GRR: 8.1% and 9.5%, respectively), perform better than the moving average models (GRR: 6.8% - table 3). The contrarian rules SG 4 to SG 6 are almost twice as profitable than the trend-following rules SG 1 to SG 3 (average GRR: 9.1% and 6.8%, respectively). Due to the frequent transactions involved in trading based on intraday data the net rate of return is roughly 4½ percentage points lower than the gross return. This difference is greater in the case of contrarian trading rules as compared to trend-following rules 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 for each class of models: Profitable positions: Number per year | Return per day | Duration in days | Unprofitable positions: Number per year | Return per day | Duration in days |
|---|---|---|---|---|---|---|---|---|---|---|
| *Moving Average* | 96.8 | 6.8 | 2.9 | 2.29 | 74.5 | 0.38 | 2.8 | 118.8 | -0.57 | 1.1 |
| *Momentum* | 99.6 | 8.1 | 0.3 | 2.53 | 147.2 | 0.42 | 1.8 | 236.7 | -0.69 | 0.5 |
| *RSIN* | 100.0 | 9.5 | 1.9 | 3.04 | 148.0 | 0.50 | 1.6 | 226.6 | -0.66 | 0.7 |
| *SG 1* | 92.9 | 5.1 | 0.3 | 1.55 | 80.3 | 0.32 | 3.4 | 155.1 | -0.51 | 1.1 |
| *SG 2* | 89.5 | 3.4 | 0.9 | 1.19 | 47.1 | 0.34 | 3.7 | 76.2 | -0.52 | 1.4 |
| *SG 3* | 100.0 | 5.9 | 2.5 | 2.32 | 65.5 | 0.47 | 2.0 | 104.6 | -0.74 | 0.7 |
| *SG 4* | 100.0 | 10.4 | 5.0 | 3.17 | 110.8 | 0.38 | 2.5 | 156.9 | -0.54 | 1.3 |
| *SG 5* | 100.0 | 7.9 | 2.6 | 2.76 | 101.9 | 0.45 | 1.9 | 161.7 | -0.66 | 0.7 |
| *SG 6* | 100.0 | 9.1 | 3.6 | 2.93 | 107.7 | 0.42 | 2.2 | 164.9 | -0.58 | 1.0 |
| *All models* | 97.3 | 7.2 | 2.6 | 2.37 | 87.4 | 0.40 | 2.6 | 138.7 | -0.59 | 1.0 |

Over the entire period between 1983 and 2007 almost all of the 2580 technical models are profitable, 97.3% of them produce a positive gross rate of return (table 3).

Table 4 classifies all models according to the t-statistic into 5 groups. 29.3% of the models achieve a t-statistic greater than 3.0, their average gross (net) rate of return amounts to 12.5%

(5.7%) per year. 29.6% of the models achieve a t-statistic between 2.0 and 3.0, they produce a gross (net) rate of return of 7.3% (3.0%) per year. Hence, 58.9% of the trading systems produce a gross rate of return significantly greater than zero over the entire sample period of 25 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.

*Table 4: Components of the profitability of 2580 trading systems by subperiods and classes of the t-statistic*

*S & 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 per year | Return per day | Duration in days | Unprofitable positions: Number per year | Return per day | Duration in days |
|---|---|---|---|---|---|---|---|---|---|---|
| *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 |
| *2001-2003* | 100.0 | 5.0 | 0.1 | 0.46 | 93.4 | 0.51 | 2.6 | 150.7 | -0.81 | 1.0 |
| *2003-2007* | 100.0 | -0.7 | -5.1 | -0.16 | 82.2 | 0.29 | 2.6 | 136.1 | -0.46 | 1.1 |
| *1983-2007* | 100.0 | 7.2 | 2.6 | 2.37 | 87.4 | 0.40 | 2.6 | 138.7 | -0.59 | 1.0 |
| *Models by t-statistic* | | | | | | | | | | |
| <0 | 2.6 | -1.2 | -3.3 | -0.44 | 36.3 | 0.24 | 5.3 | 61.0 | -0.39 | 2.1 |
| 0-<1 | 13.7 | 1.8 | -0.8 | 0.65 | 48.0 | 0.30 | 3.9 | 79.1 | -0.46 | 1.5 |
| 1-<2 | 24.8 | 4.5 | 0.9 | 1.54 | 66.4 | 0.35 | 3.0 | 106.8 | -0.52 | 1.2 |
| *2-<3.0* | 29.6 | 7.3 | 3.0 | 2.49 | 83.2 | 0.39 | 2.4 | 133.6 | -0.60 | 0.9 |
| *>3* | 29.3 | 12.5 | 5.7 | 4.03 | 132.5 | 0.51 | 1.6 | 205.9 | -0.73 | 0.7 |

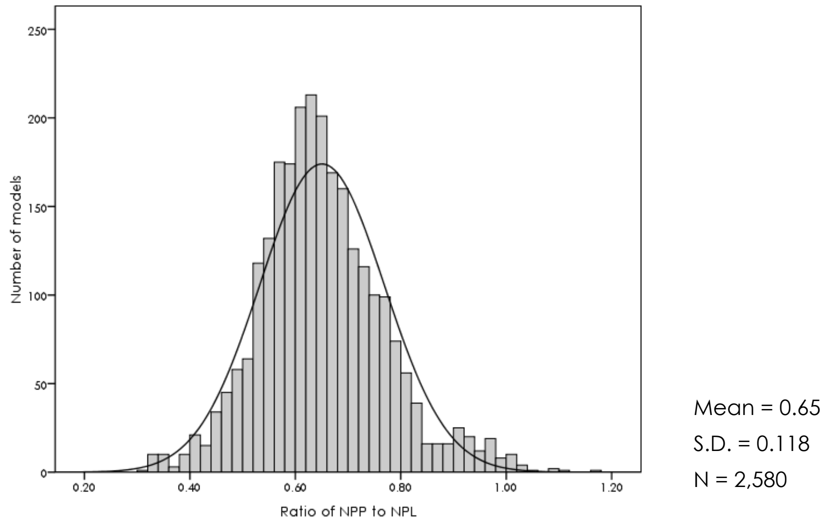
## 4.3 The pattern of profitability of the trading systems

The characteristic pattern of profitability of technical trading systems is as follows (tables 1 to 4):

- The number of profitable positions (NPP) is lower than the number of unprofitable positions (NPL).
- The average return per day during profitable positions (DRP) is smaller (in absolute terms) than the average return per day during unprofitable positions (DRL).
- The duration of profitable positions (DPP) is several times greater than the duration of unprofitable positions (DPL).

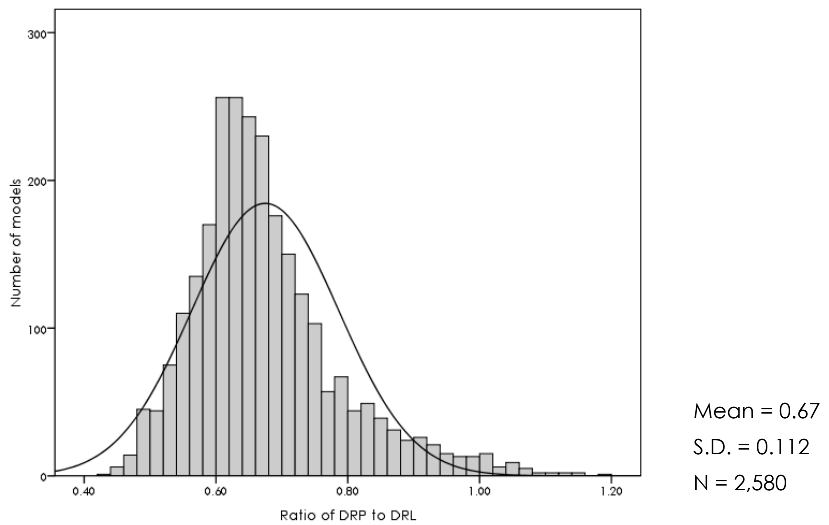
The figures 5, 6 and 7 show the distribution of the 2580 technical models by the ratios of the three profitability components, i. e., by the ratios NPP/NPL, DRP/DRL, and DPP/DPL (the means of these ratios describe the characteristic profitability pattern of technical trading systems).

*Figure 5: Distribution of 2580 trading systems by the ratio of the number of profitable positions (NPP) to the number of unprofitable positions (NPL) 1983-2000*
*S&P 500 futures market, 30-minutes-data*



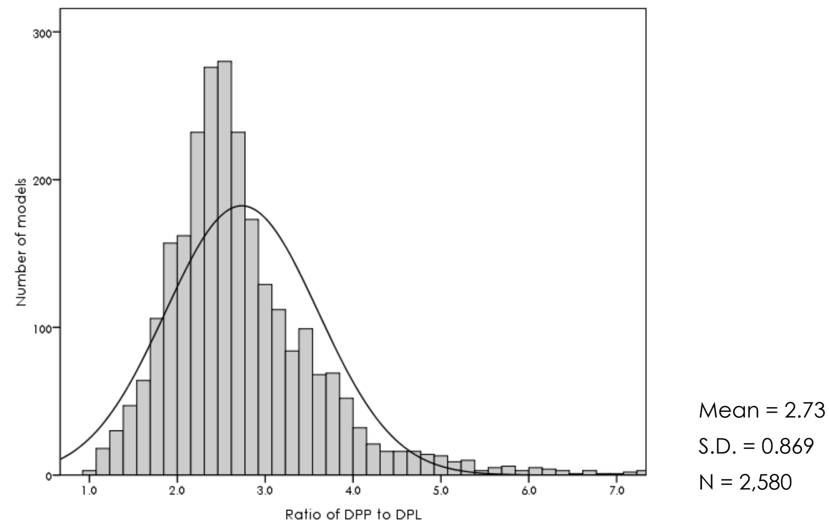

Profitable positions occur on average 35% less frequently than unprofitable positions. Figure 5 shows that cases where the number of profitable trades exceeds the number of unprofitable trades almost never occur. Also the daily return during profitable positions almost never exceeds the return during unprofitable positions. On average the former is by 33% lower than the latter (figure 6).

*Figure 6: Distribution of 2580 trading systems by the ratio of the daily return during profitable positions (DRP) to the daily return during unprofitable positions (DRL) 1983-2000*
*S&P 500 futures market, 30-minutes-data*



Hence, the high ratio between the average duration of profitable and unprofitable positions (2.73 on average) is the main reason for the profitability of technical stock trading based on 30-minutes-data (figure 7). This ratio reflects the exploitation of persistent stock price movements by technical models.

*Figure 7: Distribution of 2580 trading systems by the ratio of the duration of profitable positions (DPP) to the duration of unprofitable positions (DPL) 1983-2000*
*S&P 500 futures market, 30-minutes-data*




### 4.4 Clusters of technical models

In this section I address the following two questions: Are there groups of technical models which have a similar pattern of profitability in common? Do these groups of (relatively) homogenous models differ from each other also with respect to their overall profitability?

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 following condition: Minimize the differences between the models (with respect to the components of the profitability in our case) within each cluster and maximize the differences 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, i. e., models which "specialize" on short-term, medium-term and long-term trends in 30-minutes-stock prices.

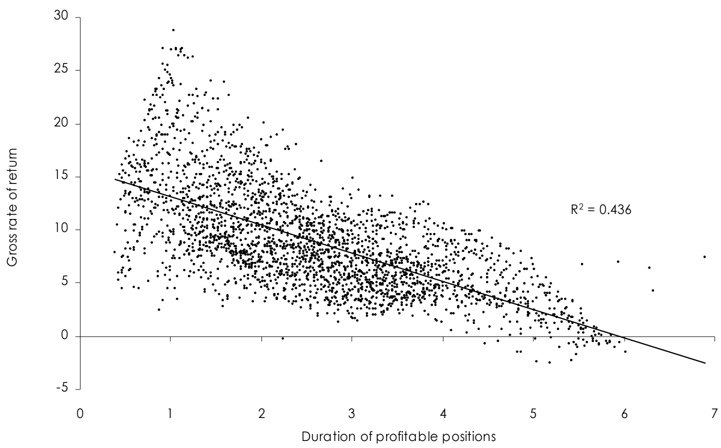
Table 5 shows the results of the cluster analysis. The 165 models of cluster 1 produce the highest number of open positions (635,3 per year on average), mainly for that reason the duration of profitable positions is relatively short (0.8 days on average). Hence, cluster 1 comprises those (fast) models which are most sensitive to price changes. AS a consequence, these models "specialize" on the exploitation of short-term price trends. The 642 models of cluster 2 signal 327.8 open positions per year, the profitable positions last 1.7 days on average. Most models belong to cluster 3 which comprises 1773 (slow) models which produce 151.3 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, 1983-2007*

| | 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* | 165 | 14.4 | 248.0 | 0.64 | 0.8 | 387.3 | -0.89 | 0.3 |
| *Cluster 2* | 642 | 10.0 | 121.6 | 0.45 | 1.7 | 206.2 | -0.70 | 0.5 |
| *Cluster 3* | 1773 | 5.4 | 60.1 | 0.36 | 3.1 | 91.2 | -0.53 | 1.2 |
| *Total* | 2580 | 7.2 | 87.4 | 0.40 | 2.6 | 138.7 | -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 14.4%. The models of cluster 2 achieve a gross rate of return (10.0%) which is also higher than the average over all 2580 models. By contrast, the comparatively slow models of cluster 3 produce an average gross rate of return of only 5.4%.

*Figure 8: Duration of profitable positions and the performance of 2,580 trading systems*
*S & P 500 futures market, 30-minutes-data, 1983-2007*




The results of the cluster analysis are confirmed by figure 8. 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 2 and 3).

### 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 8 subperiods between 1983 and 2007. 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 over the subperiods 1992/94 and 2003/07.

Table 6 compares the performance of those models which are profitable in each of the 8 subperiods ("stable models") to the performance of the other ("unstable") models. Stable models are slightly less profitable than unstable models, the former produce a gross (net) rate of return of 6.3% (2.2%) on average; the latter achieve 7.4% (2.7%). This difference is mainly due to the following "structural effect": Those types of models or signal generation which produce the highest returns like the RSIN models or SG4 (table 3) are comparatively unstable (table 6). In an analogous way, models which are less profitable than on average like the SG1-models (table 3) are comparatively stable (table 6).

*Table 6: Frequency and performance of stable and unstable trading models*
*S & P 500 futures market, 2580 models, 30-minutes-data, 1983-2007*

| 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* | 21.0 | 6.2 | 2.5 | 2.10 | 7.0 | 3.0 | 2.33 |
| *Momentum models* | 25.0 | 7.2 | -0.1 | 2.28 | 8.4 | 0.5 | 2.61 |
| *Relative strength models* | 15.8 | 6.5 | 1.3 | 2.04 | 10.0 | 2.0 | 3.23 |
| SG 1 | 30.6 | 6.5 | 1.5 | 2.02 | 4.5 | -0.2 | 1.34 |
| SG 2 | 17.3 | 5.2 | 2.3 | 1.82 | 3.0 | 0.6 | 1.06 |
| SG 3 | 18.1 | 5.0 | 1.7 | 1.92 | 6.1 | 2.6 | 2.40 |
| SG 4 | 18.8 | 7.8 | 3.7 | 2.42 | 11.0 | 5.3 | 3.34 |
| SG 5 | 19.4 | 6.2 | 1.9 | 2.20 | 8.3 | 2.8 | 2.90 |
| SG 6 | 21.6 | 6.7 | 2.2 | 2.23 | 9.7 | 4.0 | 3.12 |
| All models | 20.9 | 6.3 | 2.2 | 2.12 | 7.4 | 2.7 | 2.44 |

[1]) Stable models are profitable (GRR > 0) in each of the 8 subperiods, all others are unstable.

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

Almost all of the 2580 trading models would have produced excessive returns over the entire sample period, 20.9% of these models would have been profitable over each of 8 subperiods, 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 component 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.

*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 | 21.31 | 1.4 |
| *1989-1991* | 35.7 | 4.14 | 27.71 | 1.4 | 27.1 | 3.15 | 20.68 | 1.7 |
| *1992-1994* | 18.3 | 3.31 | 14.02 | 2.4 | 15.1 | 2.79 | 8.53 | 1.5 |
| *1995-1997* | 25.6 | 3.33 | 17.27 | 1.6 | 7.8 | 1.00 | 1.75 | 1.7 |
| *1998-2000* | 26.0 | 2.39 | 21.82 | 3.3 | 14.6 | 1.30 | 5.86 | 1.6 |
| *2001-2003* | 35.7 | 3.01 | 25.45 | 1.0 | 3.5 | 0.31 | -0.97 | 3.1 |
| *2004-2007* | 12.2 | 2.28 | 9.58 | 3.5 | 4.8 | 0.89 | -3.81 | 1.4 |
| 1986-2007[1]) | 27.8 | 3.04 | 21.57 | 2.1 | 14.5 | 1.59 | 7.62 | 1.8 |

[1]) Mean over subperods.

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 eight subperiods between 1983 and 2007 of 28.8% (all models: 7.2%).
- The ex-ante-profitability of the best models is significantly better than the average over all models. The best models achieve ex ante an average gross rate of return of 14.5% between 1986 and 2007, over the same period the gross rate of return of all models amounts to only 7.5%.

## 5. Summary and concluding remarks

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

- 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), –5.1% (1992/2000) and finally to -0.8% (2001/07). The 2580 models are even more unprofitable when trading S&P 500 futures contracts between 1983 and 2007.
- The picture is very different for stock futures trading based on 30-minutes-data. The 2580 models produce an average gross return of 7.2% per year between 1983 and 2007. Due to the high number of transactions the net rate of return is significantly lower (2.6%). Contrarian models achieve a significantly higher gross rate of return (9.1%) than trend-following models (4.8%).
- Only 2.6% of the 2580 models would have produced negative returns over the entire sample period. The probability of making an overall loss when strictly following most of these models was close to zero (the t-statistic testing the mean of the single returns against zero exceeds 2.0 in 58.9% of all models).
- The profitability of technical stock futures trading is exclusively due to the exploitation of persistent price trends around which stock prices fluctuate. This can be concluded from the profitability pattern of technical models: The number of profitable trades is lower than the number of unprofitable trades, and the return per day during profitable positions is smaller (in absolute terms) than during unprofitable positions. Hence, the overall profitability is due to profitable positions lasting several times longer than unprofitable positions.
- Tests of the performance of the trading systems over 8 subperiods between 1983 and 2007 reveal that the models would have produced profits in 4,707 out of 20,640 cases (8 subperiods times 2580 models).
- Those 25 models which performed best over the most recent subperiod produce an average gross return of 14.5% per year over the subsequent subperiod. This ex-ante-return of the best models is significantly higher than the average ex-post-return of all models (7.5%).

- Over the last two subperiods the 2580 trading systems (based on 30-minutes-data) would have performed worse than over the entire sample period, between 2004 and 2007 the models would have even produced negative gross returns on average.

The shift in the profitability of technical models from daily data to 30-minutes-data during the 1980s and – hypothetically – from 30-minutes-data to data of higher frequencies in recent years could be explained in two different ways.

According to the Adaptive Market Hypothesis (AMH) of Lo (2004), markets become gradually more efficient in an evolutionary process. By learning to exploit profit opportunities, market participants will slowly erode these opportunities through an arbitrage mechanism. Once the "old" and simpler rules have become unprofitable, new and more sophisticated trading strategies will emerge which will gradually also improve market efficiency.

An alternative interpretation is as follows. The continuous rise in the "speed" of transactions in financial markets causes technical traders to use increasingly data of higher frequencies instead of daily data.[13]) As a consequence, intraday asset price movements become more persistent and, hence, exploitable by technical models. At the same time, price changes based on daily data become more erratic which in turn causes daily models to become less profitable. In addition, the use of data of higher frequencies induces traders to use more sophisticated trading models to filter out (very) short-term trends (asset price volatility rises with data frequency). Such a shift will also impact upon the trending pattern of asset prices (for this feed-back see Schulmeister, 2006, 2007).

The main difference between the AMH and the alternative explanation sketched above is as follows. The AMH assumes that any originally profitable trading rules will become gradually less profitable because more and more people use them. As a consequence, smart traders seek for and finally discover new profitable rules. By contrast, the alternative explanation assumes that the causality runs from the use of new and more complex rules based on an ever increasing data frequency to the erosion of the profitability of the older and simpler rules. This effect is mainly due to the change in the trending pattern of asset prices caused by the gradually increasing use of the new trading strategies.[14])

[13]) Such a shift to using data of ever higher frequencies when applying (automated) trading systems has most probably contributed to the tremendous increase in transaction volume in financial markets. According to the Bank of International Settlements (BIS) stock index futures trading volume in North America rose between 2001 and 2007 from 11,911.1 bill. $ to 53,048.3 bill. $ (www.bis.org/statistics/qcsv/anx23a.csv). A great deal of these transactions might be triggered by (automated) trading systems which are increasingly based on intraday data (the number of surprising announcements has most probably not kept up with transactions).

[14]) The alternative explanation of the shift in the profitability of technical trading from daily data to higher frequency data should not be considered a "special case" of the AMH. This is so because such a shift would by no means reflect a process by which markets become gradually more efficient. Traders would still base their decisions on the information contained in past prices. Such a behavior contradicts the assumption of rational expectations and – if profitable – the assumption of weak market efficiency.

To summarize: There are two explanations for why the profitability of technical trading might gradually shift to more complex rules based on data of increasingly high frequencies. The Adaptive Market Hypothesis focuses on the arbitrage mechanism as the driving force of this process, the alternative hypothesis focuses on the self-reinforcing interaction between the type of model as well as the data frequency used, and the specific features of asset price trends. An empirical evaluation of these two hypotheses represents a complex task. Hence, it has to be left to future research.

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.

Finally, I would 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 2007). 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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