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TECHNICAL TRADING SYSTEMS AND STOCK PRICE DYNAMICS

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1. Introduction: Stock price dynamics, market efficiency and technical analysis

The debate over the informational (in)efficiency of the stock market, the predictability of returns and the exploitability of the implied pattern in stock price dynamics has intensified over the past 15 years (for an overview see Campbell, 2000; Cochran, 1999; Lo-MacKinlay, 1999; Shiller, 2000A). The difficulties in explaining certain "anomalies" in the stock market under the standard assumptions of equilibrium economics in general and the capital asset pricing model (CAPM) in particular, gave rise to a new branch in economics, "behavioral finance" or more in general "behavioral economics" (DeBondt-Thaler, 1996 Mullainathan-Thaler, 2000; Shiller, 1999; Shleifer, 2000).

In recent years the debate over the (in)efficiency of the stock market focused on two "anomalies", the momentum effect and the reversal effect. The first refers to the phenomenon that stock prices exhibit positive autocorrelation at short horizons (between 3 and 12 months) which can be profitably exploited following "momentum strategies" (Fama-French, 1989; Jegadeesh-Titman, 1993; Chan-Jegadeesh-Lakonishok, 1996; Goetzmann-Massa, 2000). The second effect refers to the negative autocorrelation of stock prices at longer horizons (between 1 and 5 years) which can be profitably exploited following "contrarian strategies" (DeBondt-Thaler, 1985 and 1987; Fama-French, 1989). In subsequent studies Jegadesh (1990), Lo-MacKinlay (1990A) and Lehman (1990) report that contrarian strategies are also profitable over short-term horizons like weeks or months.

In a statistical sense, contrarian profits could be caused in two different ways or a combination of both (Lo-MacKinlay, 1990A, and 1999, chapter 5). First, prices of individual stocks overreact to firm-specific news (this implies a negative autocorrelation of returns), and, second, there prevails a lead-lag structure in the stock market so that securities are positively cross-autocorrelated (this implies also a positive autocorrelation of stock indices).[1]) According to Lo-MacKinlay (1990A, and 1999, chapter 5) less than 50% of contrarian profits can be attributed to overreaction, the greater part of these profits is due to specific cross effects among the securities, namely, that the returns of large-capitalization stocks almost always lead those of smaller stocks.[2]) They conclude: "But a tantalizing question remains to be investigated: What are the economic sources of positive cross-autocorrelation across securities?" (Lo-MacKinlay, 1999, p. 142).

The profitability of both, momentum trading as well as contrarian trading implies the following "stylized facts" of cross-sectional stock price dynamics :

- Firm-specific information causes the price of the respective stock to underreact at first, e., g., news are only gradually incorporated into the price (accounting for the profitability of momentum strategies), and then to overreact, e. g., to overshoot the new fundamental equilibrium, followed by a reversal of the trend (accounting for a part of the profitability of contrarian strategies).
- Common news induce the same sequence of under- and overreaction in the stock market in general, however, at a different "speed": stock prices of big firms react faster to news than stock prices of smaller firms. This lead-lag-pattern contributes to the cross-autocorrelation of securities (accounting for the greatest part of contrarian profits) and consequently to the positive autocorrelation of stock price indices.
- These stock price trends - each consisting of an "underreaction component" and an "overreaction component" – occur across different time scales (over several days or weeks up to several years). As a consequence, momentum and contrarian strategies are profitable at short as well as at long horizons.

Different explanations have been offered for why stock prices exhibit momentum on the one hand, and trend reversals on the other. Chan-Jegadeesh-Lakonishok (1996) explain

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[1]) Positive index autocorrelation and lead-lag effects can also be caused by "non-synchronous trading", e. g., the fact that common stocks are not traded at the same time. However, as Lo-MacKinlay (1990B) show trading must be unrealistically "thin" in order to explain the magnitude of stock index autocorrelation.

[2]) By contrast, Jegadeesh and Titman (1995) find that contrarian profits are mainly due to "the reversal of the firm-specific component of returns", in other words, they are primarily caused by the overreaction of stock prices.

the profitability of momentum strategies primarily by two factors. First, the slow speed at which the market incorporates new information into prices (be it news concerning short-term earnings or long-term returns), and second, the trend-strengthening effect of positive feedback traders. Daniel-Titman (2000) show that investor "overconfidence" (one of the best established biases in behavioral finance) could generate stock return momentum.

Reversals of stock price trends and their exploitation through contrarian trading strategies are mainly attributed to two factors. First, the tendency of (some) investors to overreact to new information (DeBondt-Thaler, 1985 and 1987; Lakonishok-Shleifer-Vishny, 1994), and second, the positive cross-autocorrelation of stock returns (Lo-MacKinlay, 1990A), e. g., the fact that stock price indices of the overall market portfolio exhibit upward and downward trends (however, the "tantalized question" why this is the case remains still to be answered).

Several models have been developed which attempt to explain simultaneously short-term momentum and long-run reversal of stock returns. Barberis-Huang-Santos (2000) model stock market volatility in the context of the prospect theory (Kahneman-Tversky, 1979). It is assumed that the aversion to wealth losses depends on past outcomes (past success reduces the risk aversion and vice versa). The fluctuations in the price of risk then cause stock prices to systematically overshoot.

The model of Barberis-Shleifer-Vishny (1998) generates under- and overreaction of asset prices by assuming that there exist two expectational regimes in the mind of an representative investor. In the first regime dividend growth is believed to be negatively autocorrelated (hence, dividends would be mean reverting), in the second regime the opposite is believed, e.g., that dividends display trends. In the first regime stock prices underreact to dividend news (investors believe their effect to be only temporary), in the second regime stock prices overreact (investors believe dividends are trending).

In the model of Daniel-Hirshleifer-Subrahmanyam (1998) investors are overconfident, hence, they attribute to great a weight on their own private signal as compared to public information. Moreover, investors increase their overconfidence to a larger extent if public information is in line with their private signal than they reduce their overconfidence in the opposite case, e. g., when public information is inconsistent with their private beliefs ("biased self-attribution"). As a consequence, private information generates short-run overreaction which only gradually looses momentum due to the growing weight of public information about the misvaluation.

Hong-Stein (1999) assume that there are two types of agents. "Newswatchers" trade on the basis of private information about fundamentals which diffuse gradually. "Momentum investors" trade on the basis of the most recent price change. The interaction between these two groups generates both a momentum effect because news about fundamentals affect prices only gradually (reinforced by positive feedback trading) as well as an misvaluation effect because "momentum trading" drive prices beyond their fundamental equilibrium.

All these models relax the (former) mainstream assumptions about the representative agent (individual utility maximization, Bayesian learning, rational expectations) in favor of some kind of "bounded rationality" (for reasons why this concept should be incorporated in economic models see Conlisk, 1996). Bounded rationality can be assumed in very different ways. With respect to the stock market (or asset markets in general) three types of bounded rationality or even irrationality have frequently been investigated:

- First, the activities of noise traders (e. g., traders who base their transactions on economically irrelevant information) which increase the risk for rational agents and, hence, prevent prices from following its fundamental equilibrium path (Cutler-Poterba-Summers, 1991; De Long-Shleifer-Summers-Waldmann, 1990A and B; Frankel-Froot, 1990; Shleifer-Vishny, 1997).

- Second, herding behavior which has similar effects on the speculative dynamics in asset markets (Scharfenstein-Stein, 1990; Teh-De Bondt, 1997; Ottaviani-Sorensen, 2000).

- Third, emotions of individual agents and their (possibly contagious) interaction leading to "market moods" which in turn contribute to upward or downward trends in asset markets (e. g., Hirshleifer-Shumway, 2001, present impressive evidence that sunshine has a significantly positive impact on stock returns; for the informational content of the ambient noise level - the shouting of traders as indicator of their excitement - in the futures trading pit see Coval-Shumway, 1998).

Each of these types of bounded rationality (or irrationality) might contribute to asset prices moving in a sequence of persistent and overshooting trends. If this pattern can actually be exploited through momentum as well as contrarian strategies, one has to answer the following questions: "Which types of traders follow those strategies in practice? Which (trend-following) techniques are used to exploit the momentum in stock prices? Which (contrarian) techniques attempt to exploit the mean reversion in stock prices? How does the use of these techniques impact upon stock price dynamics?"

These questions have rarely be explored empirically (the analysis of the cross-sectional performance of past winners and loosers as in DeBondt-Thaler, 1985 and 1987, in Fama-French, 1989, and in similar studies, aimed at demonstrating the hypothetical profitability of momentum and contrarian strategies – in practice those approaches are actually not used). To answer the above questions one has to analyze in the first place the profitability and price effects of "technical analysis". This is so for several reasons:

- First, technical analysis is almost omnipresent in financial markets. In the foreign exchange market, e. g., surveys among market agents reveal that most transactions are influenced by technical trading techniques since agents attach to technical analysis the greatest weight at short time horizons of trading - in particular intraday trading - over which the greatest part of foreign exchange trading is done (Group of Thirty, 1985; Taylor-Allen, 1992; Wolgast, 1997; Menkhoff, 1998; Lui-Mole, 1998; Cheung-Wong, 2000). Even though similar surveys on the role of technical analysis in the stock market have not yet been undertaken, interviews with market participants (see chapter 3), inspections of the trading rooms of institutional investors, the growing demand for technical trading software as well as for books and magazines on technical stock trading show that these techniques are of great importance also in the stock markets (in the spot as well as in the derivatives markets).
- Second, technical analysis comprises specific momentum (trend-following) as well as contrarian (trend-reverting) techniques. The first try to identify persistent price trends and to jump on them at an early stage, the second try to identify "overbought" ("oversold") situations, e. g., the late stage of an upward (downward) trend (when it is "mature" for a reversal).

- Third, the execution of technical trading signals produced by trend-following models will almost certainly reinforce the current trend, the execution of signals given by contrarian models might at least contribute to a reversal of the trend.

- Fourth, an empirical exploration of the price effects of technical trading might contribute to an explanation of the cross-autocorrelation of securities prices as well as of its lead-lag structure. This is so for two reasons. First, technical analysis is particularly popular in the market for (stock index) futures where transaction costs are much lower than in the spot market (technical trading systems often use high frequency data – ranging from hourly to tick data – which involves a great number of transactions). The transmission of price movements from the futures to the spot market through index arbitrage ("program trading") might then help to answering the "tantalized question" why securities are cross-autocorrelated. Second, the fact that technical analysis is more frequently applied to stock price movements of big corporations as compared to smaller enterprises might also contribute to a better understanding of the lead-lag structure in the autocorrelation across securities.

Despite its popularity in practice technical analysis has not been analyzed empirically as the possibly most important single reason for why stock price dynamics exhibit momentum as well as mean reversion. Instead, studies have so far focused only on the possible profitability of technical trading rules in the stock market (as well as in other markets, in particular in the foreign exchange market). These studies aimed primarily at answering the question whether or not the stock market is weakly efficient (since technical analysis uses only publicly available information, almost exclusively the information contained in past prices, any excess profitability would imply that the stock market is not even weakly efficient).

Most of these studies like Goldberg-Schulmeister (1988), Schulmeister-Goldberg (1989), Brock-Lakonishok-LeBaron (1992) or Hudson-Dempsey-Keasey (1996) found technical analysis to be "abnormally" profitable in the stock market (similar results were obtained concerning technical trading in the foreign exchange market, e. g., in Schulmeister, 1987 and 1988, Levich-Thomas, 1993 and Menkhoff-Schlumberger, 1995, Schulmeister, 2000). However, the fact that the results for only relatively few trading rules were presented gave rise to the suspicion of "data snooping": the researchers might have been biased in favor of finding ex post profitable trading rules which a trader in practice would not be able to choose ex ante. This critique got support from out-of-sample tests demonstrating that trading rules which were highly profitable ex post performed significantly worse ex ante (Schulmeister, 1988; Menkhoff-Schlumberger, 1995) or became even unprofitable (Sullivan-Timmermann-White, 1999).

There are three additional shortcomings of the studies undertaken so far on the performance of technical trading systems in the stock market. First, these studies use daily data whereas technical traders have actually been switching to data of higher frequencies since the early 1980s in order to catch up with the almost continuously increasing speed of transactions (in particular in the market for stock index futures). Second, these studies do not analyze the problem of model selection by technical traders, their respective learning behavior and the related question whether or not the ex-post most profitable models remain profitable also ex-ante. Third, the causes of the profitability of technical trading systems (even if they are profitable only ex post) have not yet been investigated (in particular, it remains unclear which types of non-randomness contribute most to technical trading being profitable).

The trading behavior of different technical systems, e. g., the relationship between stock price movements, the generation of technical buy and sell signals and their impact upon subsequent price movements, have not yet been explored. This concerns in particular the following questions:

- How quickly do different trend-following systems react to changes in the direction of price movements (dependent on the type of trading rule and their parameters)?
- Are buy (sell) signals during an upward (downward) price clustered in a certain phase of the trend or are they rather smoothly distributed over the entire trend?
- How much do contrarian strategies of technical analysis – they aim at identifying "overbought" or "oversold" situations - differ from trend-following systems with respect to the process of trading signal generation?
- Do different technical trading systems trade with each other or do they mainly exert an excess demand (supply) on the stock market?

- What is the impact of the net transactions and the net positions of technical trading systems on (subsequent) stock price movements?

While it is understandable that adherents of the market efficiency hypothesis have not analyzed the trading behavior of technical analysis, it is somewhat surprising that this issue has also be neglected by adherents of "behavioral finance" (given the widespread use of technical trading systems in practice).[3])

This study aims at contributing to a better understanding of the role of technical analysis in the stock market in different respects. First, the study simulates technical stock trading on the basis of daily as well as 30-minutes-data. Second, the study tests the performance of a great variety of technical trading systems (2580) and analyzes the components of their profitability. Third, the study simulates the performance of technical stock trading not only ex post but also ex ante. Fourth, the study analyzes the impact of the interaction of different momentum as well as contrarian models on stock price dynamics.

2. Scope and structure of the study

The purpose of this study is threefold. First, it summarizes the results of a fact finding mission about the importance of technical analysis in stock trading at the New York market place. Second, the study documents the profitability of a wide range of technical trading rules ex post as well as ex ante and then analyzes the factors responsible for this profitability. Third, this study explores the relationship between the use of technical trading systems in the spot and futures market for stocks and the simultaneous and subsequent price movements. More specifically, the main objectives of this study are as follows:

- Document the role technical trading systems play in the practice of stock trading in the spot as well as in the futures market.
- Analyze the ex-post-profitability of a great number of those technical trading systems which are actually used in practice (moving average models, momentum models and relative strength models). Special attention shall be given to the components of the

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[3]) Neither textbooks on "behavioral finance" in general like Shleifer (2000) nor monographs by leading "behavioralists" on the stock market in particular like Shiller (2000A) deal with the role of technical analysis.

profitability of technical stock trading and how they are related to the pattern of stock price dynamics.

- Simulate the process of model selection based on their performance in the past and test for the ex-ante-profitability of the selected models. In particular the following questions shall be addressed: If a technical trader selects from many different models those performing best over a certain "test period" in the past, and if he/she then follows these models over the subsequent period, would he/she make "abnormal" profits? Or would this optimization strategy produce losses due to "model mining"?

- Provide an analysis of the impact of technical trading systems on stock price dynamics. This concerns in particular the following questions. How are the trading signals produced by different models distributed (clustered) over time? How many technical models are hold the same - long or short - position at any point in time? How do aggregate transactions and/or open positions of technical models and their change over time relate to the subsequent price movements?

In order to explore the interaction between technical trading and stock price dynamics in detail, the study is restricted to two stock price indices, the S&P 500 and the DAX which cover the most traded stocks in the US as well as in the German stock market. Trading shall be simulated for the spot market as well as for the futures market (the most active S&P 500 and DAX futures contract). The analysis is based on daily prices (spot and futures market) as well as on 30-minutes-data (futures market).[4])

The study covers for each market and for each data frequency the longest period for which the respective data could be obtained. Technical trading in the spot market (S&P 500 and DAX) is investigated for the period 1960 to 2000 (in this case daily data are available also for periods before 1960, however a period of 41 years seemed long enough for the purpose of this study). Trading in the S&P 500 futures market is analyzed for the period 1983 to 2000 (daily and 30-minutes-data). In the case of DAX futures trading the study covers the period 1992 to 2000 when using daily data, and 1997 to 2000 when using 30-minutes-data.

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[4]) The S&P 500 spot and futures data were provided by the Futures Industry Institute (Washington, D.C.), the respective DAX data stem from Deutsche Börse/Eurex (Frankfurt).

The remainder the study is structured as follows.

Section 3 summarizes the results of interviews with professional traders/investors of hedge funds, other investment funds, brokerage firms and investment banks about the importance of technical trading in the spot and futures markets for stocks.

Section 4 explains how (quantitative) technical trading systems like moving average models or momentum models work.

In section 5 the ex-post-profitability of 2.580 technical trading models based on daily price data is tested for the whole sample periods (spot and futures markets). The study then analyzes the components of the profitability of these systems and examines those properties of stock price movements which cause technical trading to be profitable.

Section 6 carries out the same type of analysis based on 30-minutes-data (futures markets).

Section 7 explores the ex-ante-profitability of technical trading (based on 30-minutes-data) in the following manner. The period under investigation is divided in several subperiods; then the profitability of those models which perform best over one period is tested over the subsequent period.

Section 8 investigates the influence of trading signals generated by technical models on stock price movements. An index of the aggregate transactions and open positions of the 2580 technical models is calculated at every point in time (every 30 minutes). Based on these indices the concentration of transactions on buys or sells, and of position holding on long or short is documented. Finally, the relationship between the level and the change of the position index and the subsequent stock price movements is analyzed.

Section 9 summarizes and evaluates the results of the study in the context of the controversy between the market efficiency paradigm and the behavioral finance paradigm.

3. Trading behavior in the US stock market: results of interviews with market agents

In order to collect concrete information about expectations formation and trading practices in the spot and futures market for stocks I conducted interviews with 13 professional traders/investors at the New York market place.[5]) 3 of them work for (big) investment banks, 4 for small and medium-sized hedge funds (managing capital between 1 and 3 bill. $), 3 for investment funds (managing between 300 mill. $ and 800 mill. $), and 3 work for brokerage firms. In order to receive the most detailed information it was agreed that the answers of the interview partners as well as the institutions for which they work, should be kept anonymous.

The interview was structured along some standardized questions. The partners were asked to give at first a personal answer concerning their own trading practice (the questions are also formulated in that way), and to gauge then the respective practice of other market participants.

Question 1: "Please indicate the relative share of intraday and interday trading in your overall transactions in the derivatives markets."

Only 4 out of 13 interview partners are engaged in intraday trading (2 hedge fund managers, 2 brokers). However, when asked about the respective developments in the overall market, 11 respondents believe that intraday trading has become more important over the last decade (particularly in the futures markets), supported by the internet revolution and the creation and enlargement of electronic exchanges like Globex (it organizes, e. g., the trading of the Mini-S&P 500 futures contract) or Xetra (it organizes e. g., the trading of the DAX futures contract).

Question 2 concerns the types of expectations formation: "Successful trading requires price forecasts which are sufficiently often correct. Do you form price expectations only with respect to the direction of future price movements, i.e. in a qualitative manner? Or do you attempt to quantify the price level which will prevail some minutes, hours or days ahead, i. e., do you form price expectations in a quantitative manner?"

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[5]) The interviews took place in NYC and Stamford (Connecticut) between February 22, and March 2.

10 interview partners answered that they form only directional expectations. 3 respondents (2 investment fund managers, 1 investment banker) report that they form also quantitative price expectations. However, they would not trade based on their estimation of the "fair value" of a stock (index) if the respective price moves away from this value.

As regards the stock market as a whole, all respondents believe that directional expectations formations is the rule. Some respondents mention that terms like "bullishness", "bearishness", "sideways trends", prices "heading north" or "heading south" etc. indicate that agents perceive price movements per se as the essence of the stock market (and asset markets in general), and not as – sluggish - changes in equilibrium levels.

Question 3 concerns the informational basis of transactions: "Estimate the share of those of your transactions which are triggered off by economic or political news, the share of transactions triggered off by technical trading signals, the share of transactions triggered off by arbitrage opportunities between the derivatives and the spot market and the share of transactions executed for other reasons (customer orders, „jobbing")."

Most respondents inclined to quantify these shares. However, when talking about this question it turned out that that there were only two types of traders. Only 4 respondents base their transactions primarily on technical analysis and related statistical models (e. g., time-series models) which process exclusively the information contained in past prices and - in some cases - in past volume data. The other 9 agents base their trading decisions primarily on the interpretation of economic and – in some cases – political news. Only few respondents act exclusively on just one type of information, in other words, most try to take also in consideration what the other type of trader might do (this is true for all 4 "technicians", however, 3 "news-based traders" completely disregard technical analysis).

The respondent considered themselves unable to quantify the relative importance of different trading strategies in the overall stock market, however, most of them believe that technical trading systems are increasingly used by market participants, in particular because these models can catch up with the higher speed of transactions by processing data of higher frequencies. For the same reason technical analysis is believes to be most popular in the futures markets.

Question 4 refers to two types of processing new information: "As regards the interpretation of economic news: Do you use this information according to an economic model of price determination so that you buy/sell the respective futures contract/option in order to profit from the difference between the current and the new fundamental price level? Or do you merely try to anticipate how (most) other traders might react to the new information causing the price to move upward/downward?"

Most interview partners (10 out of 13) reported that they try to anticipate the reaction of other traders to new information in order to gauge the direction of imminent price movements. However, 4 respondents mentioned that they also revise the estimated fair value of stocks according to (economic) news (even though none of them bases his/her revision on specific econometric models).

As regards the stock market as a whole all respondents believe that agents try to find out how the majority of other traders might react to news and/or to the most recent price movements (the latter generate technical trading signals which feed back upon subsequent price movements). This is believed to be the case because stock price movements are seen as the result of the transactions of all market participants.

Question 5 concerns the data frequency used for technical trading: "As regards technical trading signals: On which price data frequency do you base the interpretation of charts and/or the use of quantitative technical models like moving average models, momentum models, relative strength index, stochastics, etc.?"

Out of the 4 respondents which base their stock (futures) trading mainly on technical analysis one said that he uses intraday data, however, he refused to specify the data frequency. One respondent said his model processes tick data, the other two respondents use 15-minutes-data and 30-minutes-data, respectively.

As regards the trading practices in the stock market as a whole most respondents (11) believe that "technicians" use increasingly high frequency data (from hourly data "down" to tick data) simply because intraday trading has become more and more important, fostered by the permanent improvement of information and communication technologies and the related creation of electronic exchanges. For the same reason this "fast" technical trading is believed to be particularly popular in the stock (index) futures markets.

The next two questions concern different types of technical trading systems.

Question 6: "Which types of qualitative technical trading systems (chart techniques) do you use (bar charts, price configurations like "head and shoulders", candlesticks, others)?"

All 4 "technicians" in our sample use only quantitative models. As regards technical trading in the overall stock market, almost all respondents believe that the qualitative systems are loosing importance compared to quantitative techniques since only the latter can be used also at high data frequencies ("speed" of trading).

Question 7: "Which types of quantitative technical trading systems do you use (moving average models, momentum models, relative strength index, stochastics, other systems including statistical time-series models)?"

Only one out of 4 respondents using technical models was willing to answer this question (he uses moving average models as well as the relative strength index). All respondents considered themselves unable to estimate the relative importance of the different types of quantitative trading systems in the overall market.

Question 8 refers to the parameters of quantitative models of technical analysis (e. g., the length of moving averages): "Which length of historical prices do you use for selection/optimization of the parameters of quantitative technical models?"

The 4 "technicians" of our sample report that these "test periods" vary between 1 and 3 years which is rather long, given the fact that these traders use intraday data (two of them argued that it is "dangerous" to frequently optimize the parameters of a model).

Question 9 concerns the relationship between price movements in the spot and futures market for stocks: "As regards the arbitrage between the futures/options markets and the respective spot markets: In your opinion do price movements in most cases originate in the derivatives markets and are then transmitted to the spot market via arbitrage („program trading") or does the causality run mostly the other way around?"

4 out of 13 respondents could not give a clear answer, however, 9 believe that the causality runs in most cases from the futures to the spot market, in particular during downward price movements.

Question 10 deals with the problem of winners and losers in the stock derivatives markets: "Trading futures and options is a zero-sum-game (i. e., the sum of profits of the winners equals the sum of losses of the losers). Which types of agents are (as a group) in your opinion the winners and which are the losers (the respondents could choose multiply between different types of professional agents like investment banks, pension and other investment funds, and personal/private investors)?"

Roughly half of the respondents (6) considered themselves unable to answer this question, the 7 others believe that most probably amateur traders/investors as a group are the main losers.

The overall picture about trading practices in the stock markets which emerges from these interviews can be summarized as follows (one has, however, to keep in mind that a picture based on only 13 more or less randomly selected interviews can hardly be considered representative).

First, intraday trading has become increasingly important in the stock markets. Second, "news-based" trading and technical analysis represent the two most widely used trading techniques. In both cases price expectations are formed in a qualitative manner, e. g., about the direction of imminent price movements. Fourth, technical trading based on high frequency data (ranging from tick data to hourly data) is particularly popular in the stock (index) futures markets.

4. How technical trading systems work

Technical analysis tries to derive profitable buy and sell signals by isolating upward and downward price trends or runs around which the price fluctuates from oscillations around a stable level, called "whipsaws" in the traders' jargon (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). Since technical analysts believe that the pattern of asset price dynamics as a sequence of upward and downward 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.

One can classify technical trading systems in two different ways. First, according to the method of processing price data one can distinguish between qualitative and quantitative approaches. Second, according to the timing of trading signals one can distinguish between trend-following strategies and contrarian strategies. 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. 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.

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). The chartist trading techniques contain therefore an important subjective element (note, however, that an appropriate computer software can provide the basis for a more objective identification of chart configurations – see Chang-Osler, 1999; Osler, 2000; Lo-Mamaysky-Wang, 2000).

The quantitative approaches try to isolate price runs from non-directional movements using statistical transformations of the series 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.

4.1 Moving average models, momentum models, relative-strength-models and the six types of trading signal generation

The first type of model consists of a (unweighted) short-term moving average (MAS_j) and an 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):

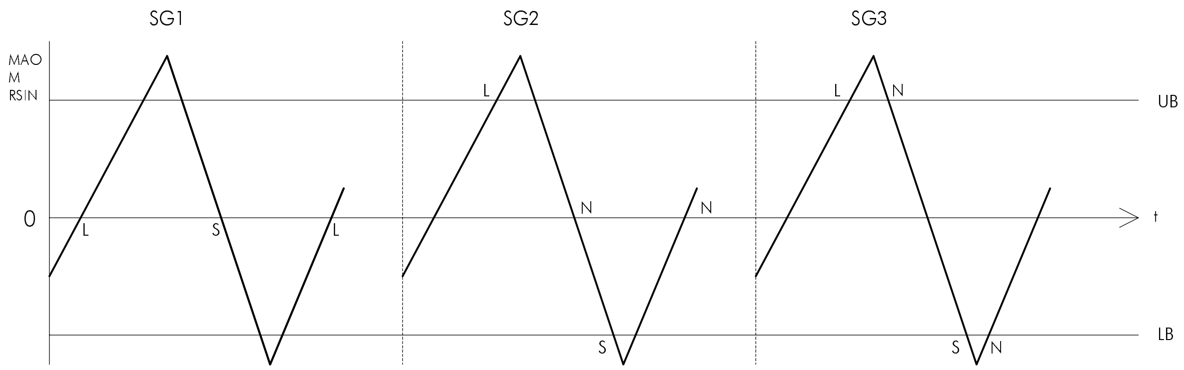
Buy (go long) when the momentum M(i) turns from negative into positive and sell (go short) in the opposite case.

The variables MAO(j,k) or M(i) are called "oscillators" because they fluctuate around zero (see e. g., the figures 1 to 3).

The basic trading rule of moving average models and momentum models (SG 1) 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).

There exist many modifications of the basic version of moving average and momentum models (see, e. g., Kaufman, 1987, chapters 5 and 6). The most common consists of a band with varying width around zero combined with different rules of opening a long, short or neutral position when the moving average oscillator or the momentum oscillator cross the upper bound, lower bound or the zero line. These rules – termed SG 2 to 6 in this study – are either trend-following or contrarian.

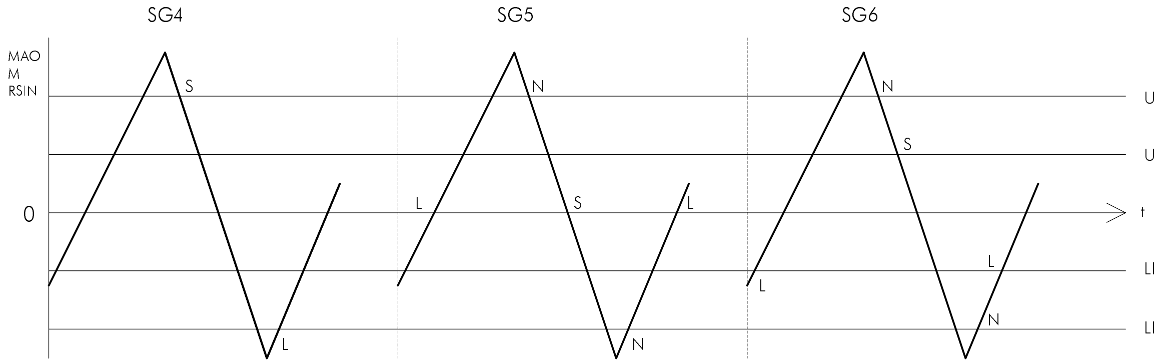
According to signal generation 2 one opens a long (short) position whenever the oscillator crosses the upper (lower) bound from below (above). When the model holds a long (short) position and the oscillator crosses the zero line from above (below) then the model switches to a neutral position. A simple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



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 (dependent on the width of the band). 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. Holding a neutral position as long as a price movement has not gained some persistence aims at avoiding losses during "whipsaws".

Rule SG 3 differs from SG 2 insofar as the former switches from an open to a neutral position earlier than the latter. Whenever the oscillator crosses the upper (lower) band from above (below) rule SG 2 turns from long (short) to neutral. Hence, when following SG 2 a trader holds a neutral position as long as the oscillator remains within the band around the zero line. This means in the case of a momentum oscillator, e. g., that one 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 can be considered contrarian since they try to identify "overbought" ("oversold") situations. A price configuration is believed to indicate an overbought situation when the moving average (momentum) oscillator is falling below a certain – still positive – level (marked by the upper bound of the band). 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 moving average or momentum 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. Model SG 6 opens a new long (short) position later than SG 4 but earlier that SG 5, SG 6 can therefore 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 Relative Strength Index is defined as follows (Kaufman, 1987, p. 99).

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

Where

$Up_t(n) = 1/n\Sigma D_i$ for $D_i>0$

$Down_t(n) = 1/n\Sigma D_i$ for $D_i<0$

and D_i is the (daily) priced 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 the persistence (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). J. Welles Wilder who has developed the Relative Strength Index concept 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).

The original RSI fluctuates between 0 and 1. 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:

$RSIN(n)_t = 1/100 [RSI(n)_t – 0,5]*2$

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 (the width of the band for the RSI as proposed by Wilder translates into an upper bound of 0,4 and a lower bound of –0,4 on the basis of the RSIN).

4.2 Assumptions concerning the simulation of technical trading in the stock markets

The simulation of technical trading in the stock market is based on the following assumptions.

With regard to the market for stock index futures it is assumed that the most liquid contract is traded. An inspection of trading statistics for the S&P 500 futures contract and for the DAX futures contract, respectively, reveals that trading volume is highest in the case of that contract which is next to expire (the so-called near-by contract). However, roughly 10 business days before expiration (on the third Friday in March, June, September and December) the trading volume of the contract which is to follow the near-by contract strongly increases and surpasses that of the near-by contract. It is therefore assumed in the simulation 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 (if the switching day falls on a holiday contracts are switched on the next following business day).

The contract switch would, however, cause the signal generating price series to exhibit a break if one simply stacked together the price series of the two contracts. The size of the gap would be the price difference between the two series on the switching day. Technical models would then misinterpret these breaks as price changes over time. In order to avoid this bias both series are joined on every switching day by indexing the prices of the contract which expires in the following quarter 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 of course 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

[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 were extracted from the tick data base).

case if one used the daily close price because any trading signal could only be executed on the next following business day at a price which differs often significantly from the close price of the previous day). Before trading is opened every day, the technical speculator knows exactly the open price at which his trading system would trigger a signal. He can therefore give a buy or sell order already in advance which ensures that any trade will be executed very shortly (usually within one minute) after the opening price has been conveyed to the trading floor. This procedure minimizes the so-called slippage costs which are incurred when prices move unfavorably between the arrival of a price generating a signal and the execution of the trade.

Commissions and slippage costs are estimated under the assumption that the technical models are used by an professional (institutional) trader for trading at electronic exchanges like Globex (Mini S&P 500 futures contract) or Xetra/Eurex (DAX futures contract). This implies commissions per transaction of roughly 0,002% when trading the S&P 500 contract and even less in the case of the DAX futures contract.[7])

Slippage costs are estimated under the (realistic) assumption that in electronic futures exchanges orders are executed within 10 seconds. An analysis of the tick data of the S&P 500 and the DAX contract prices shows that the mean of the price changes (in absolute terms) within this interval is 0,02% of contract value. If one assumes that the price moves always unfavorably when profitable trading signals are produced (e. g., the price rises after a profitable buy signal), 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%.[8])

For these reasons the simulation of technical stock futures trading operates under the assumption of overall transaction costs of 0,01% (per trade). 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

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[7]) Institutional traders pay roughly 10$ for a round trip in the S&P 500 market, and only 1,3€ in the DAX futures market. At an index value of 1000 (S&P 500) and 5000 (DAX) the value of an S&P 500 futures contract is 250.000$ and of an DAX futures contract 125.000€.

[8]) This 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.

comprised by the S&P 500 and the DAX, respectively, 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.

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% (at an index value of only 1.000 for the S&P 500, and of 5.000 in the case of the DAX, margins for institutional traders amounted to 9,2% in the S&P 500 futures market and to only 7,2% in the DAX futures market – this calculation implies a margin in absolute terms of 23.000$ for an S&P 500 contract and of 9.000€ for an DAX contract).

4.3 Performance of the three types of models over the year 2000

Figure 1a and tables 1a and 2a demonstrate how a moving average model (MAS=1, MAL=15) and a momentum model (time span i = 12) performed in the S&P 500 futures market over the year 2000.[9])

On January 3, the moving average model signals a long position and hence a S&P 500 contract is bought at an index value of 1.494,5 (the price of this contract is always 250 times the index value). Due to a sharp fall in the stock index a short position is opened the next day causing a loss of 3.0% or 3.0 cents if one assumes that there is always 1$ in the game. Even though there prevailed an (underlying) downward trend of stock prices over the months of January and February (as marked by the moving average line in figure 1a), the moving average model produced a series of unprofitable trades (except for the short position between February, 10, and March, 2).

[9]) The letters "a" and "b" attached to the number of tables or figures refer to technical trading of the S&P 500 index and the DAX index, respectively. Tables and figures concerning S&P 500 trading are embedded in the maintext, tables and figures concerning DAX trading are collected in a statistical supplement.

Figure 1a: Technical trading signals for S&P 500 futures contract 2000
Daily data

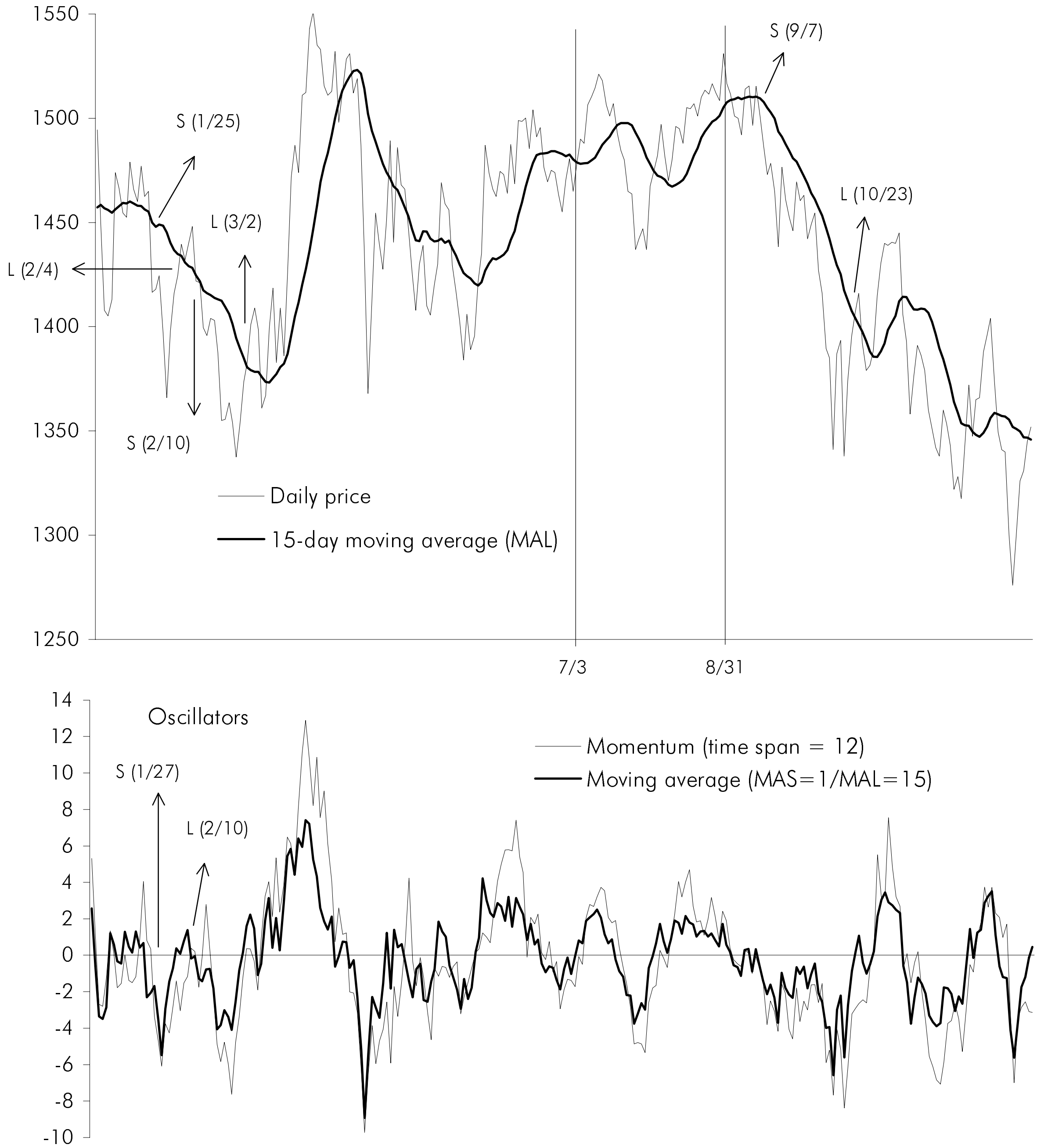


Table 1a: Performance of technical trading systems

Price series: Daily prices of the S&P500 futures contract
Begin of trading: 01/01/2000
End of trading: 12/29/2000
Signal generating process
Trading systems: Moving average (SG1)
Short-term moving average (MAS): 1
Long-term moving average (MAL): 15

The sequence of long, short and neutral positions

Date	Signal	Duration	Price	Single rate of return	Rate of return per year
01/03/2000	l	0	1,495	0.0	0.0
01/04/2000	s	1	1,450	– 3.0	– 1,086.8
01/10/2000	l	6	1,474	– 1.7	– 241.6
01/12/2000	s	2	1,455	– 1.3	– 241.5
01/14/2000	l	2	1,479	– 1.7	– 253.5
01/25/2000	s	11	1,417	– 4.2	– 196.9
02/04/2000	l	10	1,440	– 1.6	– 153.9
02/10/2000	s	6	1,422	– 1.2	– 141.3
03/02/2000	l	21	1,383	2.8	– 73.8
.	.	.	.	.	.
.	.	.	.	.	.
09/07/2000	s	30	1,501	1.3	– 46.6
09/11/2000	n	4	1,492	0.6	– 45.0
09/11/2000	s	0	1,514	0.0	– 45.0
10/23/2000	l	42	1,407	7.1	– 29.8
10/25/2000	s	2	1,392	– 1.1	– 30.9
10/30/2000	l	5	1,389	0.3	– 30.1
11/09/2000	s	10	1,406	1.3	– 27.6
12/06/2000	l	27	1,372	2.4	– 22.8
12/07/2000	s	1	1,348	– 1.8	– 24.7
12/08/2000	l	1	1,365	– 1.3	– 26.0
12/11/2000	n	3	1,366	0.1	– 25.7
12/11/2000	l	0	1,388	0.0	– 25.7
12/15/2000	s	4	1,350	– 2.8	– 28.3
12/29/2000	l	14	1,352	– 0.2	– 27.4
12/29/2000	n	0	1,352	0.0	– 27.4

The profitability of the trading system

Gross rate of return	– 27.4
Net rate of return	– 28.3
Number of positions	
Long	20.2
Short	20.2
Neutral	0
Average duration of positions	9.0
Long	7.5
Short	10.6
Neutral	0
Sum of profits	27.2
Profitable positions	
Number (NPP)	12.1
Average return	
Per position (RPP)	2.2
Per day (DRP)	0.11
Average duration (DPP)	19.7
Sum of losses	– 54.5
Unprofitable positions	
Number (NPL)	28.3
Average return	
Per position (RPL)	– 1.9
Per day (DRL)	– 0.43
Average duration (DPL)	4.5

Table 2a: Performance of technical trading systems

Price series: Daily prices of the S&P500 futures contract
Begin of trading: 01/01/2000
End of trading: 12/29/2000
Signal generating process
Trading systems: Momentum (SG1)
Time span i of M: 12

The sequence of long, short and neutral positions

Date	Signal	Duration	Price	Single rate of return	Rate of return per year
01/03/2000	l	0	1,495	0.0	0.0
01/05/2000	s	2	1,408	– 5.8	– 1,056.3
01/10/2000	l	5	1,474	– 4.7	– 546.2
01/12/2000	s	2	1,455	– 1.3	– 478.5
01/14/2000	l	2	1,479	– 1.7	– 447.4
01/18/2000	s	4	1,466	– 0.9	– 349.5
01/21/2000	l	3	1,463	0.2	– 286.4
01/27/2000	s	6	1,425	– 2.6	– 254.3
02/10/2000	l	14	1,422	0.2	– 158.9
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
09/07/2000	s	24	1,501	1.4	– 14.7
10/30/2000	l	53	1,389	8.9	– 1.4
11/09/2000	s	10	1,406	1.3	0.2
11/10/2000	l	1	1,393	0.9	1.3
11/13/2000	s	3	1,358	– 2.5	– 1.7
11/15/2000	l	2	1,391	– 2.4	– 4.4
11/16/2000	s	1	1,386	– 0.3	– 4.8
12/08/2000	l	22	1,365	1.5	– 2.9
12/14/2000	s	6	1,374	– 0.9	– 3.8
12/29/2000	n	15	1,352	1.6	– 2.0

The profitability of the trading system

Gross rate of return	– 2.0
Net rate of return	– 2.8
Number of positions	
Long	18.2
Short	18.2
Neutral	0
Average duration of positions	10.0
Long	7.7
Short	12.3
Neutral	0
Sum of profits	36.7
Profitable positions	
Number (NPP)	14.2
Average return	
Per position (RPP)	2.6
Per day (DRP)	0.16
Average duration (DPP)	16.1
Sum of losses	– 38.7
Unprofitable positions	
Number (NPL)	22.2
Average return	
Per position (RPL)	– 1.7
Per day (DRL)	– 0.28
Average duration (DPL)	6.2

Figure 2a: Technical trading signals for S&P 500 futures contrac
July and August 2000, 30-minutes-data

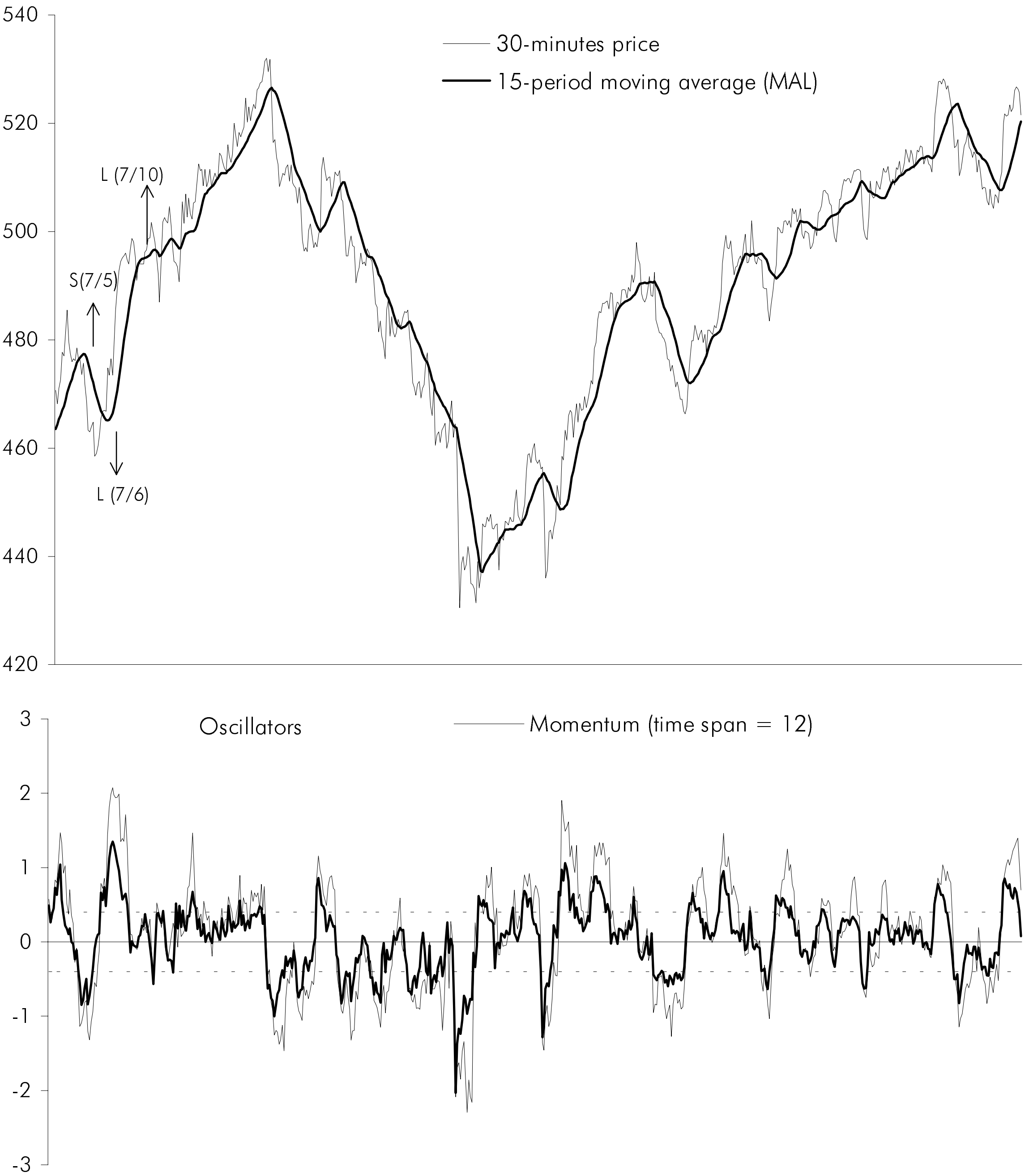


Table 3a: Performance of technical trading systems
Price series: 30-minutes prices of the S&P500 futures contract
Begin of trading: 01/01/2000
End of trading: 12/29/2000
Signal generating process
Trading systems: Moving average (SG1)
Short-term moving average (MAS): 1
Long-term moving average (MAL): 15

The sequence of long, short and neutral positions

Date	Signal	Duration	Price	Single rate of return	Rate of return per year
08:30:34/01/03/2000	l	0	1,496.4	0.0	0.0
09:00:03/01/03/2000	s	0.02	1,481.0	– 1.0	– 1,8346.4
15:00:06/01/03/2000	l	0.25	1,468.5	0.8	– 249.8
08:30:07/01/04/2000	s	0.73	1,451.0	– 1.2	– 502.7
13:00:01/01/05/2000	l	1.19	1,416.5	2.4	167.0
08:30:28/01/06/2000	s	0.81	1,406.5	– 0.7	35.9
.	.	.	.	.	.
.	.	.	.	.	.
11:30:16/07/05/2000	s	4.85	1,476.3	0.5	50.3
12:00:01/07/06/2000	l	1.02	1,466.8	0.6	51.3
08:30:16/07/10/2000	s	3.85	1,491.0	1.7	53.4
09:00:07/07/10/2000	l	0.02	1,494.2	– 0.2	53.0
09:30:30/07/10/2000	s	0.02	1,494.0	– 0.0	53.0
11:00:05/07/10/2000	l	0.06	1,496.2	– 0.2	52.7
14:29:59/07/10/2000	s	0.15	1,495.5	– 0.1	52.6
09:30:27/07/11/2000	l	0.79	1,501.8	– 0.4	51.5
12:30:10/07/11/2000	s	0.12	1,497.2	– 0.3	50.9
08:30:20/07/12/2000	l	0.83	1,505.5	– 0.6	49.6
12:30:03/07/13/2000	s	1.17	1,509.6	0.3	49.8
13:00:09/07/13/2000	l	0.02	1,514.5	– 0.3	49.2
15:00:01/07/17/2000	s	4.08	1,524.0	0.6	49.4
09:00:04/07/20/2000	l	2.75	1,500.8	1.5	51.5
.	.	.	.	.	.
.	.	.	.	.	.
12:59:59/12/26/2000	s	4.94	1,321.5	2.2	37.0
13:30:06/12/26/2000	l	0.02	1,324.5	– 0.2	36.7
11:00:02/12/28/2000	s	1.9	1,346.0	1.6	38.2
12:00:00/12/28/2000	l	0.04	1,346.5	– 0.0	38.1
13:00:05/12/28/2000	s	0.04	1,346.5	0.0	38.1
13:31:03/12/28/2000	l	0.02	1,348.2	– 0.1	38.0
14:30:15/12/28/2000	s	0.04	1,346.8	– 0.1	37.9
15:00:06/12/28/2000	l	0.02	1,350.5	– 0.3	37.6
10:30:03/12/29/2000	s	0.81	1,344.5	– 0.4	37.1
11:00:05/12/29/2000	l	0.02	1,348.2	– 0.3	36.8
11:30:20/12/29/2000	s	0.02	1,347.4	– 0.1	36.7
13:30:12/12/29/2000	n	0.08	1,344.8	0.2	36.9

The profitability of the trading system

Gross rate of return	36.9
Net rate of return	27.8
Number of positions	
Long	225.3
Short	225.3
Neutral	0
Average duration of positions	0.8
Long	0.7
Short	0.9
Neutral	0
Sum of profits	159.7
Profitable positions	
Number (NPP)	136.4
Average return	
Per position (RPP)	1.2
Per day (DRP)	0.65
Average duration (DPP)	1.8
Sum of losses	– 122.7
Unprofitable positions	
Number (NPL)	314.3
Average return	
Per position (RPL)	– 0.4
Per day (DRL)	– 1.03
Average duration (DPL)	0.4

Table 4a: Performance of technical trading systems

Price series: 30-minutes prices of the S&P500 futures contract
Begin of trading: 01/01/2000
End of trading: 12/29/2000
Signal generating process
Trading systems: Momentum (SG1)
Time span i of M: 12

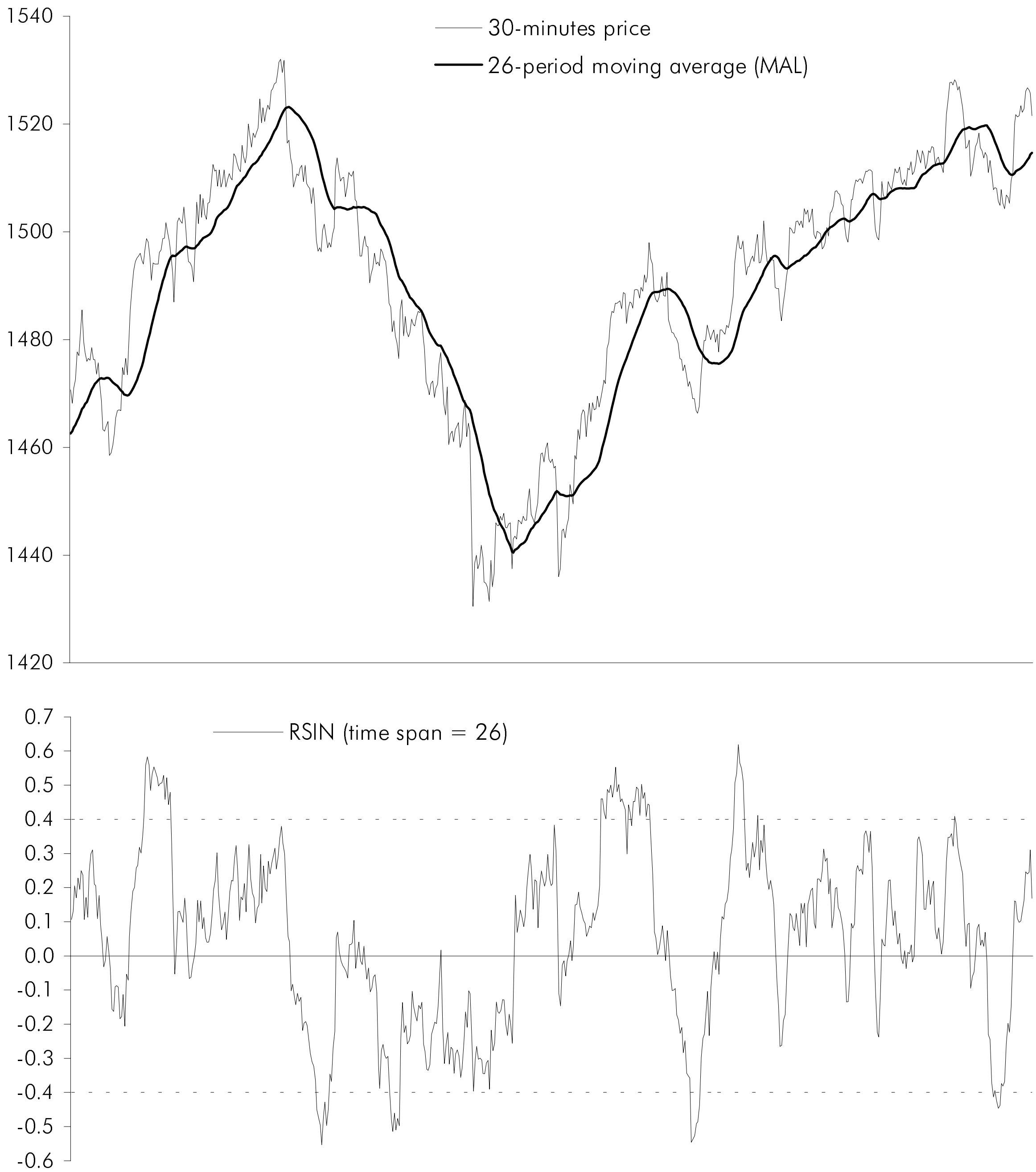
The sequence of long, short and neutral positions

Date	Signal	Duration	Price	Single rate of return	Rate of return per year
08:30:34/01/03/2000	l	0.00	1,496.4	0.0	0.0
09:00:03/01/03/2000	s	0.02	1,481.0	– 1.0	– 1,8346.4
13:30:04/01/05/2000	l	2.19	1,420.8	4.1	501.8
08:30:28/01/06/2000	s	0.79	1,406.5	– 1.0	246.9
09:00:14/01/06/2000	l	0.02	1,407.0	– 0.0	240.9
09:30:02/01/06/2000	s	0.02	1,407.0	0.0	239.3
10:00:01/01/06/2000	l	0.02	1,414.8	– 0.6	171.6
15:00:09/01/10/2000	s	4.21	1,469.5	3.9	266.4
09:00:01/01/11/2000	l	0.75	1,470.1	– 0.0	239.6
10:30:01/01/11/2000	s	0.06	1,468.3	– 0.1	232.2
08:30:12/01/13/2000	l	1.92	1,451.0	1.2	230.7
.	.	.	.	.	.
.	.	.	.	.	.
08:30:34/12/18/2000	l	4.79	1,343.0	3.2	40.5
13:30:04/12/18/2000	s	0.21	1,343.5	0.0	40.5
14:00:00/12/18/2000	l	0.02	1,342.9	0.0	40.5
14:30:15/12/18/2000	s	0.02	1,336.5	– 0.5	40.0
09:00:01/12/19/2000	l	0.77	1,349.5	– 1.0	38.9
14:29:59/12/19/2000	s	0.23	1,333.5	– 1.2	37.7
11:00:22/12/21/2000	l	1.85	1,303.5	2.3	39.8
11:29:59/12/28/2000	s	7.02	1,343.3	3.1	42.1
12:00:00/12/28/2000	l	0.02	1,346.5	– 0.2	41.9
12:30:00/12/29/2000	s	1.02	1,343.2	– 0.3	41.5
15:00:00/12/29/2000	n	0.10	1,333.5	0.7	42.2

The profitability of the trading system

Gross rate of return	42.2
Net rate of return	34.1
Number of positions	
Long	200.0
Short	200.0
Neutral	0
Average duration of positions	0.9
Long	0.8
Short	1.0
Neutral	0
Sum of profits	150.4
Profitable positions	
Number (NPP)	140.4
Average return	
Per position (RPP)	1.1
Per day (DRP)	0.62
Average duration (DPP)	1.7
Sum of losses	– 108.2
Unprofitable positions	
Number (NPL)	259.7
Average return	
Per position (RPL)	– 0.4
Per day (DRL)	– 0.88
Average duration (DPL)	0.5

Figure 3a: Technical trading signals for S&P 500 futures contract
July and August 2000, 30-minutes-data



The strong fluctuations of daily stock prices together with the fact that a trend-following trading rule like SG 1 always lags behind these price movements, caused the moving average model to produce many more unprofitable than profitable trades. Only over the last 4 months of the year 2000 was the model profitable due to the exploitation of two significant downward trends of stock prices (figure 1a and table 1a). For the year as a whole the moving average model produced an huge negative gross return (-27,4%).[10])

The momentum model performed better, mainly due to a more efficient timing of the trading signals (their number is roughly the same as in the case of the moving average model). However, also the momentum model produced an overall loss (table 2a).

If one compares stock price movements based on daily data to the movements based on 30-minutes-data over July and August 2000 then the following observation can be made (see figures 1a and 2a for the S&P 500, and figures 1b and 2b for the DAX, respectively). What seems to be erratic fluctuations or even jumps on the basis of daily data shows up as a sequence of persistent upward or downward runs on the basis of 30-minutes-data (sometimes interrupted by "whipsaws"). As a consequence, technical models will perform better over this period when based on 30-minutes-data as compared to daily data. Generally speaking, technical trading systems will work best based on that data frequency where price movements are most persistent. This might be daily data at a time when persistent intraday price movements occurred rather seldom (because intraday trading was not yet important), or this might be minute data or even tick data when the "speed" of trading has become particularly high.

The fact that the same type of moving average model and momentum model perform much better over the year 2000 when based on 30-minutes-data as compared to daily data can be taken as a first confirmation of this hypothesis (compare tables 1a/b and 2a/b to tables 3a/b and 4a/b). In the S&P 500 futures market the MA model (1/15) and the momentum model (12) produce a gross rate of return of 36.9% and 42.2%, respectively. Due to the high number of transactions the net rate of return is markedly lower, namely 27.8% and 34.1%, respectively (tables 3a and 4a). When trading DAX futures (based on 30-minutes-data) these models performed even better, they produced a

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[10]) The rate of return per year at time t (R_t)is calculated as the annual sum of all single returns (r_i):

$R_t = (\Sigma r_i)*(365/D_t)$, where D_t denotes the cumulative duration of the trading period.

gross rate of return of 48.2% and 54.2%, respectively (the net rates of return amount to 35.7% and 41.6%, respectively – tables 3b and 4b).

Figures 2a/b makes it particularly clear that the profitability of technical trading is due to exploiting relatively few though persistent stock price runs. The size of the respective profits can compensate for the more frequent single losses incurred during "whipsaws" which are comparatively small because the price fluctuations are small. E. g., the sum of the 2 profits from holding first a short and then a long position during the downward and upward run between July 5 and July 10 (S&P 500) was much greater than the sum of 6 consecutive losses which the MA model (1/15) produced during the subsequent "whipsaws" (figure 2a and table 3a).

Figures 3a/b shows how an RSIN oscillator (time span n = 26) based on 30-minutes-data fluctuates over July and August 2000. A comparison of the trading signals produced by the (contrarian) RSIN model according to SG 4 and the trading signals of the (trend-following) MA model (1/26) according to SG 1 shows that the former signals a new open position in most cases earlier than the MA model (some of these trading signals are marked in the chart). In order to facilitate a similar comparison of trading signals between the trend-following rules (SG 1 to SG 3) on the one hand, and contrarian rules (SG 4 to SG 6) on the other hand in the case of moving average and momentum oscillators, an upper and lower bound has also be drawn in figure 2a.

> The profitability of any trading system can be split into its components in the following way (components of profits and losses as well as the overall rates of return are calculated in this study on an annualized base, hence, the expression "per year" is mostly omitted). 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. Gross profits (per year) can be split into three components, the number of profitable positions per year (NPP), the average return (profit) per day during profitable positions (DRP), and the average duration of profitable in days (DPP). The product of the two latter components gives the average return per profitable position (RPP). Similarly, gross losses (per year) can be decomposed into the number of unprofitable positions per year (NPL), the average return (loss) per day during unprofitable positions (DRL), and the average

duration of unprofitable in days (DPL). The product of the two latter components gives the average return (loss) per unprofitable position (RPL).

The following relationship holds:

GRR = NPP*DRP*DPP – NPL*DRL*DPL = NPP*RPP – NPL*RPL

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). The analysis of the profitability of technical trading systems in the stock markets focuses on the components of gross profits/losses in order to facilitate comparisons of the results across types of models and data frequencies (the number f transactions varies considerably in these respects).

The structure of the profitability of the moving average and momentum models over the year 2000 as shown in tables 1a/b to 4a/b is as follows. All models produce many more single losses than single profits (single losses occur almost twice as frequently than single profits). Moreover, the average return per day (in absolute terms) during unprofitable positions is much higher than during profitable positions (even in the case of the highly profitable 30-minutes-models). The overall profitability of the 30-minutes-models is therefore due to the fact that the duration of profitable positions lasts roughly four times longer than the unprofitable positions. This profitability pattern is typical also for daily models – their performance over the year 2000 was unprofitable because the average return (e. g., per time unit) during unprofitable positions exceeds the average return during profitable positions by a much larger margin in the case of daily models as compared to 30-minutes-models. This is explained by the fact that over the year 2000 stock price movements on the basis of 30-minutes-data were much more persistent than on the basis of daily data (e. g., price "jumps" were much more pronounced in the case of daily data as compared to 30-minutes-data – see figures 1 and 2 show).

4.4 Performance of the six different trading rules between 1983 and 2000

Tables 5a/b and 6a/b show the performance of the 6 different trading rules (SG 1 to 6) for the same type of moving average model (MAS = 1, MAL = 15), momentum model (time span = 12) and RSIN model (time span =15), respectively, on the basis of daily data as well as on the basis of 30-minutes-data. The simulation refers to trading S&P 500 futures and DAX futures, respectively, over the entire sample period.

The performance of the 3 technical models does not differ strongly across trading rules when daily data are used (the returns are negative in almost all cases in the S&P 500 futures market, however, in the DAX market moving average and momentum models perform comparatively better). This is particularly true for the moving average model and the momentum model mainly because the range between the upper and lower band is rather narrow given the wide fluctuations of both oscillators on the basis of daily data (by construction, the amplitude of the RSIN-oscillator depends much less on the data frequency).[11]) The structure of the (negative) profitability varies across trading rules in the following way. The trend-following systems (SG 1 to SG 3) produce less trading signals than the contrarian systems (SG 4 to SG 6), hence, the average duration of open positions is longer in the case of trend-following systems as compared to contrarian systems (at the same time the latter perform somewhat better than the former).

The picture is very different when trading the same models is simulated on the basis of 30-minutes-data. First, all models and trading rules are highly profitable. Second, the rates of return differ significantly across trading rules. Third, the number of trading signals and, hence, the average duration of open positions varies considerably across trading rules. The trend-following rules SG 1 to SG 3 produce less trading signals than the contrarian rules SG 4 to SG 6. At the same time the ratio between the number of profitable and unprofitable positions is mostly lower in the case of the trend-following rules as compared to the contrarian rules. This is one important reason for why the trend-following rules are less profitable than the contrarian rules when trading is based on 30-minutes-data, in particular in the S&P 500 market. Fourth, the ratio between the daily return during profitable and unprofitable positions is mostly lower in the case of trend-following rules as compared to contrarian rules (this is the second reason for why the trend-following rules perform worse than the contrarian rules).

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[11]) In order to avoid the suspicion of „model mining" identical model parameters are used across types of trading rules, data frequencies and markets.

Table 5a: Pattern of technical trading in the S&P 500 futures market, daily data, 1983-2000

	SG1	SG2[1])	SG3[1])	SG4[1])	SG5[1])	SG6[2])
Moving average models (MAS = 1, MAL = 15)						
Gross rate of return	– 10.1	– 10.3	– 10.7	– 10.4	– 10.3	– 10.5
Sum of profits	23.5	21.6	21.8	26.1	23.6	24.9
Profitable positions						
Number	9.3	7.7	9.1	14.5	11.3	12.7
Average return						
Per position	2.5	2.8	2.4	1.8	2.1	2.0
Per day	0.11	0.11	0.12	0.11	0.12	0.11
Average duration in days	23.4	25.8	20.3	16.1	18.1	17.2
Sum of losses	– 33.5	– 31.9	– 32.5	– 36.5	– 33.9	– 35.4
Unprofitable positions						
Number	29.3	22.9	28.5	34.7	32.6	33.8
Average return						
Per position	– 1.1	– 1.4	– 1.1	– 1.1	– 1.0	– 1.1
Per day	– 0.23	– 0.23	– 0.25	– 0.28	– 0.26	– 0.27
Average duration in days	5.0	6.1	4.6	3.8	4.0	3.9
Single rates of return						
Mean	– 0.26	– 0.34	– 0.29	– 0.21	– 0.23	– 0.23
t-statistic	– 2.97	– 3.11	– 3.31	– 3.06	– 3.10	– 3.12
Median	– 0.60	– 0.82	– 0.59	– 0.48	– 0.49	– 0.49
Standard deviation	2.31	2.54	2.24	2.06	2.12	2.09
Skewness	2.88	2.63	2.77	2.96	2.93	2.94
Excess kurtosis	15.97	12.90	15.30	17.67	17.31	17.52
Sample size	696	552	676	885	790	838
Momentum models (Time span = 12)						
Gross rate of return	– 7.6	– 7.2	– 8.4	– 10.1	– 9.0	– 9.3
Sum of profits	24.6	22.9	23.1	26.5	24.7	25.6
Profitable positions						
Number	11.1	9.4	11.6	14.6	12.7	14.1
Average return						
Per position	2.2	2.4	2.0	1.8	2.0	1.8
Per day	0.11	0.11	0.12	0.12	0.13	0.12
Average duration in days	19.6	21.7	16.7	14.7	15.6	14.9
Sum of losses	– 32.3	– 30.1	– 31.5	– 36.6	– 33.7	– 34.9
Unprofitable positions						
Number	24.4	21.1	24.2	30.7	27.7	29.1
Average return						
Per position	– 1.3	– 1.4	– 1.3	– 1.2	– 1.2	– 1.2
Per day	– 0.22	– 0.21	– 0.23	– 0.24	– 0.23	– 0.24
Average duration in days	6.1	6.8	5.8	4.9	5.4	5.0
Single rates of return						
Mean	– 0.22	– 0.24	– 0.23	– 0.22	– 0.22	– 0.21
t-statistic	– 2.15	– 2.07	– 2.45	– 2.81	– 2.57	– 2.62
Median	– 0.53	– 0.61	– 0.50	– 0.46	– 0.48	– 0.44
Standard deviation	2.53	2.66	2.43	2.27	2.34	2.29
Skewness	2.52	2.38	2.56	2.82	2.68	2.75
Excess kurtosis	13.06	11.75	14.52	16.76	15.59	16.37
Sample size	638	550	644	814	727	778
Relative strength models (Time span = 12)	SG4[1])	SG5[1])	SG6[2])	SG4[3])	SG5[3])	SG6[4])
Gross rate of return	– 0.6	– 4.4	– 2.4	1.3	– 3.7	– 1.5
Sum of profits	31.2	22.6	27.9	28.8	21.2	25.7
Profitable positions						
Number	14.2	13.1	14.4	10.5	11.4	11.2
Average return						
Per position	2.2	1.7	1.9	2.7	1.9	2.3
Per day	0.15	0.17	0.16	0.14	0.18	0.15
Average duration in days	15.2	10.3	12.3	19.2	10.2	14.9
Sum of losses	– 31.8	– 27.0	– 30.3	– 27.5	– 24.9	– 27.2
Unprofitable positions						
Number	22.4	23.2	23.8	18.2	21.0	20.6
Average return						
Per position	– 1.4	– 1.2	– 1.3	– 1.5	– 1.2	– 1.3
Per day	– 0.21	– 0.29	– 0.25	– 0.17	– 0.29	– 0.22
Average duration in days	6.6	4.1	5.0	9.0	4.1	5.9
Single rates of return						
Mean	– 0.02	– 0.12	– 0.06	0.04	– 0.11	– 0.05
t-statistic	– 0.15	– 1.42	– 0.68	0.33	– 1.17	– 0.44
Median	– 0.38	– 0.38	– 0.34	– 0.44	– 0.40	– 0.40
Standard deviation	2.63	2.19	2.38	3.08	2.34	2.63
Skewness	1.83	3.02	2.36	2.15	2.82	2.27
Excess kurtosis	13.50	25.59	17.65	13.37	21.80	14.09
Sample size	659	653	687	516	583	573

1) UB1 = LB1 = 0.3. – [2]) UB1 = LB1 = 0.3, UB2 = LB2 = 0.15. – [3]) UB1 = LB1 = 0.4. – [4]) UB1 = LB1 = 0.4, UB2 = LB2 = 0.2.

Table 6a: Pattern of technical trading in the S&P 500 futures market, 30-minutes data, 1983-2000

	SG1	SG2[1]	SG3[1]	SG4[1]	SG5[1]	SG6[2]
Moving average models (MAS = 1, MAL = 15)						
Gross rate of return	17.8	10.5	16.2	27.0	22.4	24.6
Sum of profits	105.5	73.2	73.8	131.4	100.4	117.7
Profitable positions						
Number	134.8	81.9	120.2	205.4	180.5	196.6
Average return						
Per position	0.8	0.9	0.6	0.6	0.6	0.6
Per day	0.44	0.46	0.67	0.57	0.63	0.60
Average duration in days	1.8	2.0	0.9	1.1	0.9	1.0
Sum of losses	– 87.7	– 62.7	– 57.6	– 104.5	– 78.0	– 93.1
Unprofitable positions						
Number	333.7	133.1	221.2	320.7	317.0	332.2
Average return						
Per position	– 0.3	– 0.5	– 0.3	– 0.3	– 0.3	– 0.3
Per day	– 0.70	– 0.74	– 1.07	– 0.78	– 0.97	– 0.82
Average duration in days	0.4	0.6	0.2	0.4	0.3	0.3
Single rates of return						
Mean	0.04	0.05	0.05	0.05	0.05	0.05
t-statistic	4.20	2.76	4.57	6.35	5.83	6.10
Median	– 0.12	– 0.21	– 0.09	– 0.11	– 0.09	– 0.11
Standard deviation	0.83	1.10	0.82	0.79	0.73	0.75
Skewness	4.53	2.95	4.17	3.53	4.33	3.96
Excess kurtosis	222.44	131.97	276.36	210.47	297.96	258.30
Sample size	8,432	3,869	6,144	9,470	8,956	9,518
Momentum models (Time span = 12)						
Gross rate of return	16.3	13.5	16.2	23.7	19.9	22.7
Sum of profits	100.2	79.5	83.4	122.1	100.2	111.8
Profitable positions						
Number	150.8	92.0	154.5	240.6	205.2	226.9
Average return						
Per position	0.7	0.9	0.5	0.5	0.5	0.5
Per day	0.43	0.44	0.55	0.52	0.55	0.54
Average duration in days	1.5	2.0	1.0	1.0	0.9	0.9
Sum of losses	– 83.9	– 66.0	– 67.1	– 98.3	– 80.4	– 89.2
Unprofitable positions						
Number	272.2	153.9	225.3	332.8	297.7	320.4
Average return						
Per position	– 0.3	– 0.4	– 0.3	– 0.3	– 0.3	– 0.3
Per day	– 0.63	– 0.61	– 0.87	– 0.75	– 0.83	– 0.79
Average duration in days	0.5	0.7	0.3	0.4	0.3	0.4
Single rates of return						
Mean	0.04	0.06	0.04	0.04	0.04	0.04
t-statistic	3.89	3.40	4.25	5.59	4.99	5.51
Median	– 0.10	– 0.13	– 0.07	– 0.06	– 0.06	– 0.06
Standard deviation	0.87	1.08	0.83	0.75	0.75	0.75
Skewness	2.05	1.53	2.10	2.33	2.33	2.38
Excess kurtosis	163.55	116.36	213.34	212.50	239.60	229.73
Sample size	7,614	4,426	6,836	10,322	9,053	9,853

Relative strength models (Time span = 12)	SG4[1]	SG5[1]	SG6[2]	SG4[3]	SG5[3]	SG6[4]
Gross rate of return	27.0	21.7	27.1	26.2	21.3	25.4
Sum of profits	125.8	94.1	112.58	118.9	86.7	106.6
Profitable positions						
Number	219.5	193.8	211.88	180.2	175.4	182.2
Average return						
Per position	0.6	0.5	0.5	0.7	0.5	0.6
Per day	0.54	0.59	0.58	0.53	0.64	0.60
Average duration in days	1.1	0.8	0.9	1.2	0.8	1.0
Sum of losses	– 98.8	– 72.4	– 85.46	– 92.7	– 65.4	– 81.2
Unprofitable positions						
Number	291.6	278.6	291.9	236.8	250.6	254.4
Average return						
Per position	– 0.3	– 0.3	– 0.3	– 0.4	– 0.3	– 0.3
Per day	– 0.75	– 0.89	– 0.79	– 0.66	– 0.86	– 0.73
Average duration in days	0.5	0.3	0.4	0.6	0.3	0.4
Single rates of return						
Mean	0.05	0.05	0.05	0.06	0.05	0.06
t-statistic	6.08	5.81	6.49	6.15	6.43	6.57
Median	– 0.06	– 0.06	– 0.06	– 0.06	– 0.06	– 0.06
Standard deviation	0.83	0.73	0.79	0.89	0.68	0.79
Skewness	3.36	2.88	4.31	4.07	5.33	5.44
Excess kurtosis	196.99	304.54	260.383	103.22	190.69	151.83
Sample size	9,200	8,504	9096	7,506	7,669	7,859

1) UB1 = LB1 = 0.3. – [2]) UB1 = LB1 = 0.3, UB2 = LB2 = 0.15. – [3]) UB1 = LB1 = 0.4. – [4]) UB1 = LB1 = 0.4, UB2 = LB2 = 0.2.

The following trading pattern is common to all types of models, trading rules and data frequencies shown in the tables 5a/b and 6a/b (36 cases per market):

- The number of unprofitable trades is always significantly higher than the number of profitable trades (in most cases by more than 50%).
- The average (negative) return per day during unprofitable positions is much greater (in absolute terms) than during profitable positions.
- Profitable positions last on average 3 to 5 times longer than unprofitable positions.

The overall profitability of the models when based on 30-minutes-data is therefore due to the exploitation of persistent stock price runs. The smaller fluctuations often cause technical models to produce losses, which, however, are small, precisely because the fluctuations are small. Thus, the profits from the correct identification of the few, but persistent price movements compensate for the more frequent, but much smaller losses stemming from minor stock price fluctuations.

The distribution of the single rates of return reflect the profitability pattern of technical models (tables 5a/b and 6a/b):

- The median is negative.
- The standard deviation is several times higher than the mean.
- The distribution is skewed to the right and extremely leptokurtotic (very large and very small single returns occur more often than implied by the normal distribution).

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). Since the t-statistic shown in tables 6a/b exceeds 3.0 in most cases one can conclude that the probability of making an overall loss by following the trading signals of most of the slected models over the entire sample period was less than 0.05%.[12])

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[12]) In a strict sense t-statistics can not be used if a sample distribution is significantly leptokurtotic. For this study, however, this is less problematic since the distribution of the single rates of return produced by technical trading systems is at the same time skewed to the right (this holds true for every single model included in the study). The coincidence of this skewness with an excess kurtosis implies that the number of

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 (since traders are assumed not to invest own capital the risk-free rate has to be neglected when calculating the Sharpe ratio). If, e. g., two trading rules produce the same ratio between the average of single returns and their standard deviation (the Sharpe ratio) 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. For the same reason the t-statistic enables one to quantify the level of the probability of making an overall loss by following a specific trading rule (in contrast to the Sharpe ratio).[13])

5. The performance of technical trading systems based on daily price data over the whole sample period

This section investigates a great variety of technical models so that their trading behavior can be analyzed comprehensively. 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 and which are therefore not used in practice. 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

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relatively large losses is actually smaller than in the case of a symmetric distribution. Hence, the actual probability of making an overall loss should be smaller than the probability calculated on the basis of the t-distribution.

[13]) The Sharpe ratio 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 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 actually used in practice by professional traders to help them in changing strategic positions. Even though stock dealers revealed in informal interviews that moving average models with MAS longer than 10 days and MAL longer than 30 days as well as momentum models with a time span of more than 30 days are rarely used (these models signal too few trades), a wider parameter range was chosen in order to analyze also the behavior of slower models. However, models with moving averages of 50, 150 or even 200 days (as simulated in the study by Brock-Lakonishok-LeBaron, 1992) have not been tested because those extremely slow models are not used in practice.[14])

[14]) In the S&P 500 spot market the moving average rules (1/150), (5/150), (1/200) and (2/200) would have signaled only 7.4, 3.9, 5.8 and 4.0 open positions per year between 1960 and 2000. This are much less open positions than professional stock traders usually incur. In addition, these slow rules would have been less profitable than those (faster) models which are used in practice. This result is in line with the finding of Sullivan-Timmermann-White (1999) that relatively shorter moving averages performed mostly better than those tested by Brock-Lakonishok-LeBaron, 1992.

Table 7a: Pattern of technical trading in the S&P 500 spot market, daily data, 1960-2000

		SG1	SG2[1])	SG3[1])	SG4[1])	SG5[1])	SG6[2])
Moving average models	MAS	1	2	1	12	5	1
	MAL	6	5	12	40	35	20
Gross rate of return		17.5	5.5	9.6	5.3	1.3	9.1
Sum of profits		41.2	30.2	27.6	16.1	16.9	26.8
Profitable positions							
Number		20.9	15.7	11.7	3.2	3.9	10.3
Average return							
Per position		2.0	1.9	2.4	5.0	4.3	2.6
Per day		0.16	0.16	0.13	0.07	0.08	0.11
Average duration in days		12.4	11.7	18.1	74.3	57.3	24.5
Sum of losses		– 23.8	– 24.8	– 18.0	– 10.9	– 15.6	– 17.7
Unprofitable positions							
Number		28.7	23.1	21.0	4.8	8.0	21.8
Average return							
Per position		– 0.8	– 1.1	– 0.9	– 2.3	– 1.9	– 0.8
Per day		– 0.22	– 0.23	– 0.18	– 0.09	– 0.13	– 0.18
Average duration in days		3.7	4.7	4.7	26.5	15.4	4.6
Single rates of return							
Mean		0.35	0.14	0.29	0.66	0.11	0.28
t-statistic		7.68	2.64	4.61	2.27	0.57	4.00
Median		– 0.23	– 0.31	– 0.31	– 0.69	– 0.97	– 0.33
Standard deviation		2.07	2.13	2.33	5.23	4.35	2.55
Skewness		2.68	2.13	2.94	1.94	2.49	3.53
Excess kurtosis		13.85	12.25	14.29	4.40	7.94	18.47
Sample size		2,034	1,589	1,340	327	487	1,315
Momentum models (time span)		5	18	13	3	35	28
Gross rate of return		11.8	6.9	4.8	12.8	5.4	6.3
Sum of profits		36.2	22.6	24.9	46.1	18.9	21.5
Profitable positions							
Number		16.9	7.6	10.5	31.1	6.7	7.9
Average return							
Per position		2.1	3.0	2.4	1.5	2.8	2.7
Per day		0.15	0.09	0.11	0.19	0.08	0.09
Average duration in days		14.6	31.5	22.0	7.8	37.5	31.6
Sum of losses		– 24.3	– 15.7	– 20.2	– 33.3	– 13.5	– 15.2
Unprofitable positions							
Number		24.8	12.4	16.4	39.8	11.1	12.8
Average return							
Per position		– 1.0	– 1.3	– 1.2	– 0.8	– 1.2	– 1.2
Per day		– 0.20	– 0.14	– 0.19	– 0.27	– 0.13	– 0.14
Average duration in days		4.8	9.0	6.4	3.1	9.5	8.7
Single rates of return							
Mean		0.28	0.35	0.18	0.18	0.31	0.31
t-statistic		5.04	2.95	2.15	5.68	2.28	2.58
Median		– 0.24	– 0.42	– 0.30	– 0.15	– 0.29	– 0.28
Standard deviation		2.33	3.35	2.74	1.71	3.61	3.45
Skewness		2.91	3.16	2.52	2.03	3.51	3.46
Excess kurtosis		19.64	14.62	10.64	10.69	16.18	16.34
Sample size		1,708	821	1,102	2,908	726	845
		SG4[1])	SG5[1])	SG6[2])	SG4[3])	SG5[3])	SG6[4])
Relative strength models (Time span)		13	14	28	9	26	11
Gross rate of return		8.0	6.3	3.5	8.7	0.0	8.5
Sum of profits		32.4	23.8	19.3	35.4	13.1	28.8
Profitable positions							
Number		14.9	12.8	7.7	17.0	6.0	14.4
Average return							
Per position		2.2	1.9	2.5	2.1	2.2	2.0
Per day		0.13	0.14	0.11	0.15	0.13	0.15
Average duration in days		16.6	13.2	22.1	13.5	17.1	13.7
Sum of losses		– 24.3	– 17.5	– 15.9	– 26.7	– 13.1	– 20.4
Unprofitable positions							
Number		18.6	16.7	11.6	20.6	10.2	17.6
Average return							
Per position		– 1.3	– 1.1	– 1.4	– 1.3	– 1.3	– 1.2
Per day		– 0.21	– 0.24	– 0.14	– 0.20	– 0.18	– 0.21
Average duration in days		6.4	4.4	9.9	6.6	7.1	5.4
Single rates of return							
Mean		0.24	0.21	0.18	0.23	0.00	0.26
t-statistic		3.51	3.36	1.79	3.65	0.01	4.01
Median		– 0.22	– 0.18	– 0.34	– 0.17	– 0.36	– 0.13
Standard deviation		2.53	2.20	2.85	2.48	2.56	2.39
Skewness		1.46	2.15	1.96	1.52	2.50	1.69
Excess kurtosis		6.06	9.69	7.23	6.67	14.00	9.67
Sample size		1,370	1,207	788	1,540	661	1,313

[1]) UB1 = LB1 = 0.3. – [2]) UB1 = LB1=0.3, UB2 = LB2 = 0.15. – [3]) UB1 = LB1 = 0.4. – [4]) UB1 = LB1 = 0.4, UB2 = LB2=0.2.

5.1 Technical stock trading in the spot market

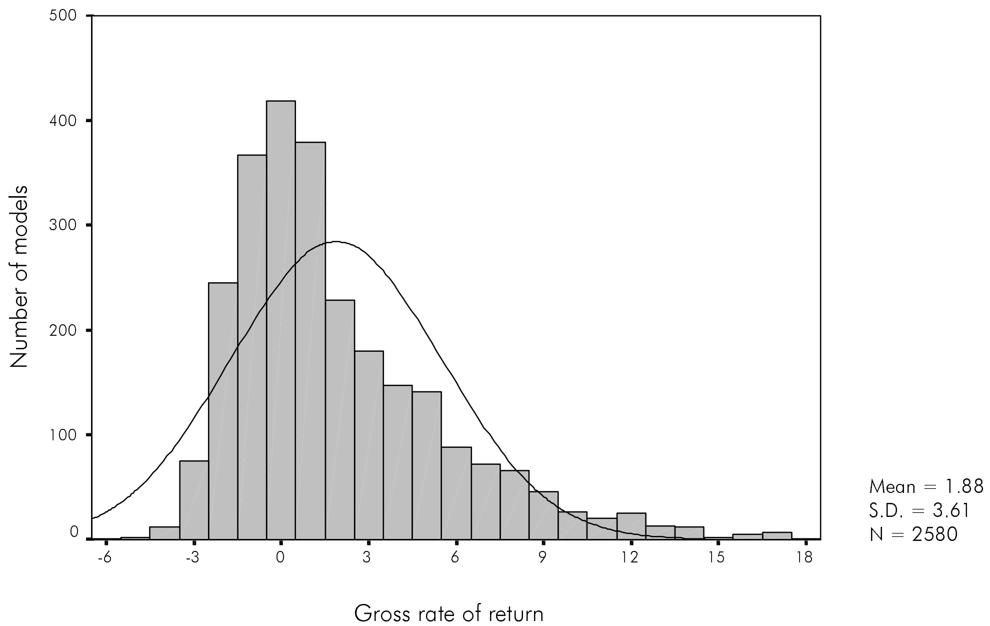
5.1.1 *Overview of the performance of 2580 trading systems*

Tables 7a and 7b compare the performance of 6 moving average models, 6 momentum models and 6 RSIN models in the S&P 500 and the DAX spot market between 1960 and 2000 (daily data). The models were chosen in such a way as to cover wide ranges of moving average lengths and time spans as well as the six different types of trading signal generation. As a consequence the selected models are very different with respect to their price sensitivity and hence the number of trading signals. Most models display an average duration of profitable positions between 10 and 20 days (they focus on the exploitation of short-term stock price trends like the moving average model (1/6/SG 1), the momentum model (3/SG 4) or the RSIN model (11/SG 6) in the case of S&P 500 trading). Some of the selected models display an average duration of profitable positions between 20 and 40 days, only relatively few specialize on the exploitation of long-term stock price trends like the moving average model (5/35/SG 5).

Several interesting observations can be made from tables 7a and 7b. First, the profitability of technical trading varied remarkably across the 18 tested models. All models were profitable except for one RSIN model (time span = 26/SG 5) which produced an annual return of exactly 0,0% in the S&P 500 market. The difference in the gross rate of return between the worst and the best performing models amounted to 17,5 percentage points in S&P 500 trading and to 15,8 percentage points in DAX trading. Second, the best performing models are at the same time those models which "specialize" on riding short-term price trends (these models can also be called "fast" since they react quickly to price changes and, hence, produce comparatively many trading signals). In the S&P 500 market, e. g., the two best performing models show a duration of profitable positions of only 12,4 days and 7,8 days, respectively. At the same time, most models which perform relatively poorly, display a comparatively long duration of open positions (this observation does, however, not hold true for RSIN models which are generally fast models). Third, the number of profitable positions is always smaller than the number of unprofitable positions. Fourth, the average return per day during profitable positions is much 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). Fifth, the average duration of profitable positions is several times greater than that of unprofitable positions.

The simulation of the same models in the DAX spot market displays a very similar trading pattern in spite of the fact that the average profitability is in most cases higher than in the S&P 500 market (table 7b). This trading pattern is typical for technical models in general (as will be demonstrated later). Hence, any profitability of technical trading systems stems exclusively from the successful exploitation of persistent price movements.

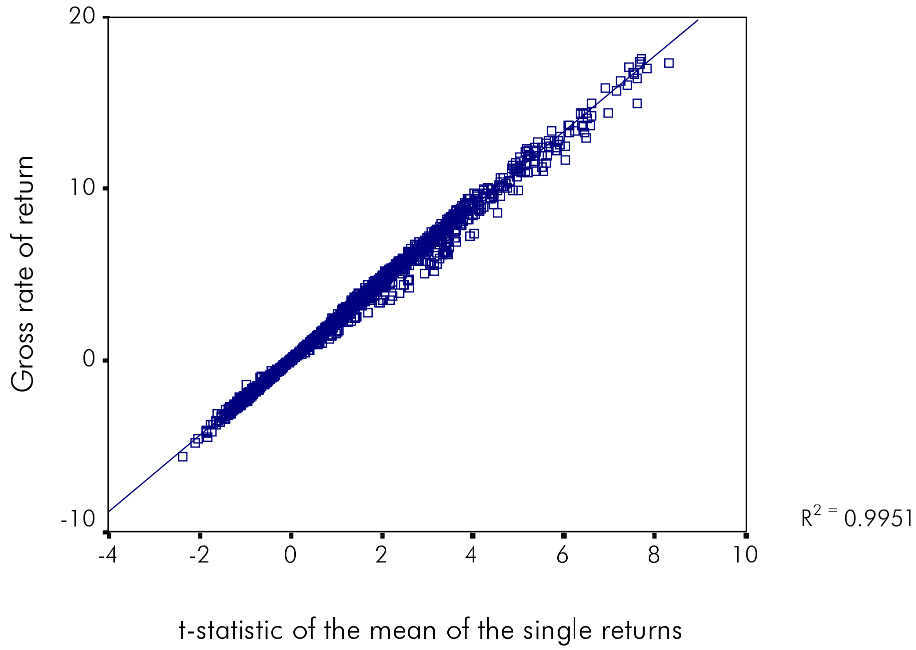
Figure 4a: Distribution of 2580 trading systems by the gross rate of return 1960-2000
S&P 500 spot market, daily data



Figures 4a and 4b show the distribution of all 2580 trading systems by their annual gross rates of return over the entire sample period. On average they produce a return of (only) 1.9% per year in the case of S&P 500 trading, and of 8.6% in the case of DAX trading, respectively. The standard deviation amounts to 3.61 (S&P 500) and 3.10 (DAX), respectively. The best performing models produce an annual return of roughly 12% in the S&P 500 market and of roughly 18% in the DAX market, respectively. The worst models produce an annual loss of roughly 4% (S&P 500) and of 1% (DAX), respectively.

The t-statistic of the mean of the single rates of return amounts to 0.84 on average in the case of S&P 500 trading, and to 2.91 in the case of DAX trading, respectively (tables 8a/b). There prevails a very close linear relationship between the gross rates of return and the t-statistic: the more profitable a model is the smaller is the probability of making an overall loss (figures 5a/b).

Figure 5a: Profitability and riskiness of 2580 technical trading systems 1960-2000
S&P 500 spot market, daily data



5.1.2 *The performance by different types of models and trading rules*

Tables 8a and 8b classify all models by type of model and trading rule and report their performance as well as the components of their profitability. The following observations can be made. First, the average performance of all models is rather poor in the S&P 500 market, the average gross rate of return (GRR) amounts to only 1.9% per year. However, in the DAX market the models perform significantly better (average GRR: 8.6%). Second, in both markets the momentum models perform best, their average gross rate of return amounts to 5.6% (S&P 500) and to 10.3% (DAX), respectively. Third, the performance of the momentum models is mainly due to the fact that these models realize the highest ratio between the average duration of profitable and unprofitable positions.

Table 8a: Components of the profitability of technical trading by types of models
S & P 500 spot market, daily data, 1960-2000

Signal generation	Profitable models	Models	Share of profitable models	Gross rate of return	t-statistic	Mean and standard deviation[15]) for each class of models					
						Profitable positions			Unprofitable positions		
						Number	Return per day	Duration in days	Number	Return per day	Duration in days
Moving average models											
SG 1	220	354	62.1	1.0	0.45	5.3	0.08	50.4	10.4	– 0.14	15.0
				(3.0)	*(1.31)*	*(2.5)*	*(0.02)*	*(16.8)*	*(4.4)*	*(0.03)*	*(5.8)*
SG 2	198	354	55.9	0.6	0.28	4.6	0.08	52.5	8.7	– 0.14	16.6
				(2.5)	*(1.14)*	*(2.0)*	*(0.02)*	*(17.2)*	*(3.5)*	*(0.03)*	*(6.2)*
SG 3	214	354	60.5	1.1	0.49	5.3	0.09	43.8	10.0	– 0.15	13.4
				(2.9)	*(1.34)*	*(2.6)*	*(0.02)*	*(16.5)*	*(4.2)*	*(0.03)*	*(5.4)*
SG 4	222	354	62.7	1.8	0.77	6.7	0.09	42.4	12.2	– 0.15	12.8
				(3.8)	*(1.67)*	*(3.6)*	*(0.02)*	*(16.0)*	*(5.3)*	*(0.03)*	*(5.3)*
SG 5	208	354	58.8	1.4	0.62	6.0	0.09	42.6	11.3	– 0.15	12.7
				(3.4)	*(1.53)*	*(3.0)*	*(0.02)*	*(16.0)*	*(4.9)*	*(0.03)*	*(5.2)*
SG 6	213	354	60.2	1.6	0.70	6.3	0.09	42.5	11.7	– 0.15	12.7
				(3.6)	*(1.61)*	*(3.3)*	*(0.02)*	*(16.0)*	*(5.1)*	*(0.03)*	*(5.2)*
Total	1,275	2,124	60.0	1.2	0.55	5.7	0.09	45.7	10.7	– 0.15	13.9
				(3.3)	*(1.45)*	*(3.0)*	*(0.02)*	*(16.9)*	*(4.8)*	*(0.03)*	*(5.7)*
Momentum models											
SG 1	38	38	100.0	5.3	2.24	9.0	0.10	31.5	15.2	– 0.15	8.7
				(2.3)	*(1.03)*	*(4.2)*	*(0.03)*	*(10.4)*	*(5.8)*	*(0.03)*	*(2.4)*
SG 2	38	38	100.0	4.7	2.01	7.7	0.10	35.4	13.2	– 0.15	9.8
				(2.1)	*(0.97)*	*(3.7)*	*(0.03)*	*(12.1)*	*(5.0)*	*(0.03)*	*(2.8)*
SG 3	38	38	100.0	5.3	2.30	9.4	0.10	28.9	14.8	– 0.16	8.1
				(2.2)	*(1.05)*	*(4.6)*	*(0.03)*	*(10.2)*	*(5.3)*	*(0.04)*	*(2.4)*
SG 4	38	38	100.0	6.4	2.67	11.7	0.10	24.7	18.1	– 0.17	6.9
				(2.4)	*(1.06)*	*(5.5)*	*(0.03)*	*(8.1)*	*(6.4)*	*(0.04)*	*(1.9)*
SG 5	38	38	100.0	5.8	2.51	10.6	0.10	26.5	16.5	– 0.17	7.4
				(2.3)	*(1.08)*	*(5.1)*	*(0.03)*	*(9.1)*	*(5.9)*	*(0.04)*	*(2.1)*
SG 6	38	38	100.0	6.1	2.59	11.2	0.10	25.5	17.3	– 0.17	7.2
				(2.3)	*(1.07)*	*(5.3)*	*(0.03)*	*(8.6)*	*(6.2)*	*(0.04)*	*(2.0)*
Total	228	228	100.0	5.6	2.39	9.9	0.10	28.8	15.9	– 0.16	8.0
				(2.3)	*(1.06)*	*(4.9)*	*(0.03)*	*(10.4)*	*(6.0)*	*(0.04)*	*(2.5)*
Relative strength models											
SG 4	51	76	67.1	3.6	1.52	10.8	0.12	25.3	14.7	– 0.14	15.3
				(5.6)	*(2.41)*	*(7.4)*	*(0.03)*	*(11.2)*	*(7.9)*	*(0.06)*	*(10.4)*
SG 5	70	76	92.1	4.3	2.33	10.5	0.14	14.8	14.4	– 0.20	6.1
				(3.6)	*(1.80)*	*(5.8)*	*(0.02)*	*(3.3)*	*(6.7)*	*(0.04)*	*(2.0)*
SG 6	58	76	76.3	4.3	2.05	10.9	0.13	19.4	15.1	– 0.17	9.6
				(4.4)	*(2.09)*	*(6.6)*	*(0.02)*	*(6.8)*	*(7.0)*	*(0.06)*	*(4.8)*
Total	179	228	78.5	4.1	1.97	10.8	0.13	19.8	14.8	– 0.17	10.3
				(4.6)	*(2.13)*	*(6.6)*	*(0.03)*	*(8.9)*	*(7.2)*	*(0.06)*	*(7.7)*
All models											
SG 1	258	392	65.8	1.4	0.62	5.7	0.08	48.6	10.8	– 0.14	14.4
				(3.2)	*(1.39)*	*(2.9)*	*(0.02)*	*(17.2)*	*(4.8)*	*(0.03)*	*(5.9)*
SG 2	236	392	60.2	1.0	0.45	4.9	0.08	50.9	9.1	– 0.14	16.0
				(2.8)	*(1.24)*	*(2.4)*	*(0.02)*	*(17.5)*	*(3.9)*	*(0.03)*	*(6.3)*
SG 3	252	392	64.3	1.5	0.67	5.7	0.09	42.3	10.4	– 0.15	12.8
				(3.1)	*(1.42)*	*(3.1)*	*(0.02)*	*(16.6)*	*(4.6)*	*(0.03)*	*(5.4)*
SG 4	311	468	66.5	2.4	1.05	7.7	0.10	38.2	13.1	– 0.15	12.7
				(4.3)	*(1.85)*	*(5.0)*	*(0.02)*	*(16.5)*	*(6.1)*	*(0.04)*	*(6.5)*
SG 5	316	468	67.5	2.2	1.05	7.1	0.10	36.8	12.2	– 0.16	11.2
				(3.7)	*(1.72)*	*(4.3)*	*(0.03)*	*(17.7)*	*(5.6)*	*(0.04)*	*(5.3)*
SG 6	309	468	66.0	2.4	1.07	7.5	0.10	37.4	12.7	– 0.15	11.7
				(4.0)	*(1.78)*	*(4.6)*	*(0.03)*	*(17.0)*	*(5.8)*	*(0.04)*	*(5.3)*
Total	1,682	2,580	65.2	1.9	0.84	6.5	0.09	41.9	11.5	– 0.15	13.0
				(3.6)	*(1.62)*	*(4.0)*	*(0.02)*	*(17.9)*	*(5.4)*	*(0.03)*	*(6.0)*

[15]) In parentheses.

Tables 9a and 9b classify all models according to their performance as measured by the t-statistic into five groups and quantify the components of profitability for each of them. When trading in the S&P 500 market, 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).

The distribution of the 2580 models by their t-statistic is different in the case of DAX trading due to their better performance as compared to S&P 500 trading. Over the entire sample period only 1.5% of all models produce losses. Most models generate a t-statistic between 2.0 and 3.0 (average GRR: 7.6%), 38.0% of the models realize a t-statistic greater than 3.0, these models produce an average gross rate of return of 11.4% per year.

The pattern of profitability is the same for each class of models and each market. The number of single losses exceeds the number of single profits, the average return per day is higher during unprofitable positions than during profitable positions, so that the overall profitability is due to the profitable positions lasting three to four times longer than the unprofitable positions.

Tables 9a and 9b show also the performance of the 2580 trading systems over 4 subperiods since 1960. The subperiods were chosen in such a way as to ensure that the results of the simulation of technical stock trading in the spot markets can be compared to the results regarding technical stock futures trading. Since data on stock index futures were available only for the period beginning in the year 1983 (S&P 500) and in the year 1992 (DAX), respectively, these two years were taken as the beginning of the last two subperiods.

The profitability of technical models does not display a clear trend over the four subperiods since 1960 in the case of DAX trading (it was highest between 1960 and 1971, lowest between 1972 and 1982, and stabilized in the last two subperiods around the average gross rate of return over the entire sample period). However, in the case of S&P 500 trading the average gross rate of return has clearly declined from 8.6% (1960/71) to 2.0% (1972/82), -0.0% (1983/91) and finally to –5.1% (1992/2000).

Table 9a: Components of the profitability of 2,580 trading system by classes of the t-statistic and subperiods

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

t-statistic of the mean of the single returns	Number of models	Relative share in %	Gross rate of return	t-statistic	Mean for each class of models					
					Profitable positions			Unprofitable positions		
					Number	Return per day	Duration in days	Number	Return per day	Duration in days
1960-1971										
<0	14	0.5	– 1.5	– 0.42	5.2	0.09	32.4	8.2	– 0.10	20.3
0-<1	636	24.7	2.6	0.68	4.6	0.07	51.1	6.7	– 0.12	17.7
1-<2	624	24.2	5.4	1.44	4.7	0.07	55.7	6.5	– 0.10	17.9
2-<3.0	543	21.0	9.7	2.50	6.1	0.08	44.3	8.0	– 0.11	11.9
>3	763	29.6	15.8	4.24	10.7	0.10	29.1	12.6	– 0.14	6.9
Total	2580	100.0	8.6	2.30	6.8	0.08	44.2	8.7	– 0.12	13.3
1972-1982										
<0	1047	40.6	– 3.7	– 0.78	5.4	0.10	41.4	10.4	– 0.17	14.1
0-<1	789	30.6	2.1	0.45	4.9	0.09	52.4	8.9	– 0.14	16.0
1-<2	402	15.6	6.8	1.51	8.2	0.11	32.2	13.1	– 0.16	9.2
2-<3.0	210	8.1	10.9	2.42	9.9	0.12	27.9	15.4	– 0.17	6.6
>3	132	5.1	17.7	3.92	17.9	0.16	16.1	23.5	– 0.21	4.3
Total	2580	100.0	2.0	0.45	6.7	0.10	40.9	11.5	– 0.16	12.8
1983-1991										
<0	1416	54.9	– 1.9	– 0.36	5.5	0.10	41.8	11.3	– 0.15	15.0
0-<1	1070	41.5	1.8	0.34	7.0	0.11	40.4	14.3	– 0.16	12.1
1-<2	93	3.6	6.8	1.29	15.0	0.15	16.4	22.1	– 0.22	6.2
2-<3.0	1	0.0	11.4	2.11	10.8	0.15	20.5	13.6	– 0.15	10.6
>3	-	-	-	-	-	-	-	-	-	-
Total	2580	100.0	– 0.0	– 0.01	6.4	0.11	40.3	12.9	– 0.16	13.5
1992-2000										
<0	2238	86.7	– 6.2	– 1.36	6.1	0.09	39.0	14.5	– 0.16	12.1
0-<1	326	12.6	1.7	0.37	6.7	0.08	49.7	10.4	– 0.13	18.1
1-<2	12	0.5	5.2	1.26	20.8	0.14	14.8	32.9	– 0.22	5.4
2-<3.0	4	0.2	9.6	2.34	25.3	0.16	9.2	35.8	– 0.23	3.3
>3	-	-	-	-	-	-	-	-	-	-
Total	2580	100.0	– 5.1	– 1.12	6.3	0.09	40.2	14.1	– 0.16	12.8
1960-2000										
<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
Total	2580	100.0	1.9	0.84	6.5	0.09	41.9	11.5	– 0.15	13.0

The tendency of a declining profitability of technical trading based on daily data – it is documented in Schulmeister (2000) also for the currency markets - might be the result of the growing use of new information and communication technologies which have improved the access to information, lowered transaction costs and increased liquidity in financial markets. However, the higher "speed" of trading and the related shortening of the time horizon of expectations formation could account for the declining profitability of technical trading based on daily data in two different ways.

In the first case, one could argue that the information and communication technologies made markets more efficient thereby eliminating profit opportunities for technical trading strategies. This argument implies that these profit opportunities were due to new information being too sluggishly incorporated into prices (in this case prices move frequently in persistent runs, whereas in an efficient market they move in "jumps" as instantaneous reactions to news).

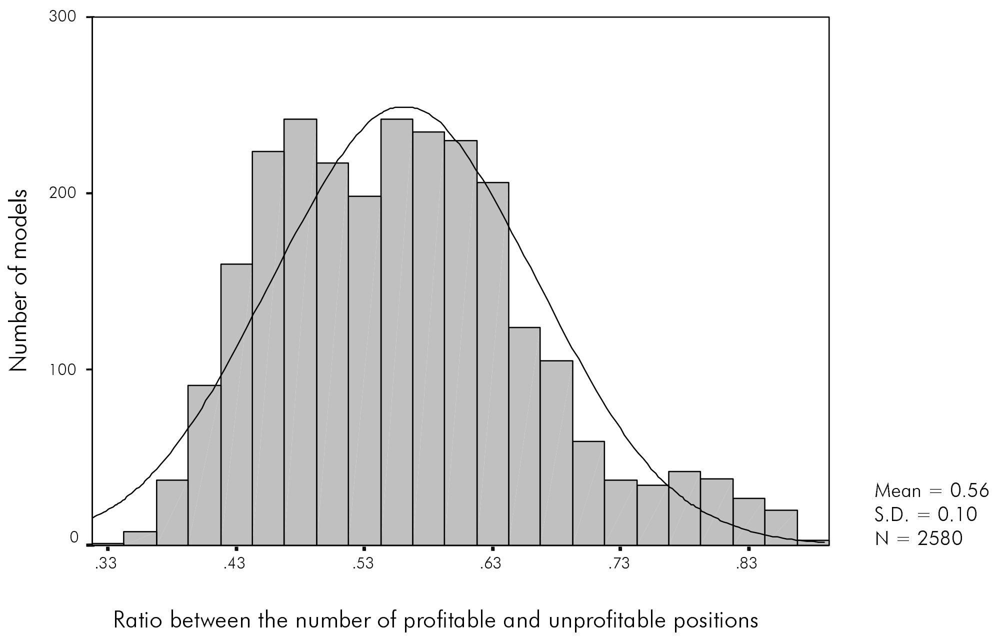
In the second case, one could argue that the new technologies enabled more and more traders to use technical models on the basis of high frequency (intraday) data instead of daily data. The increasing importance of technical intraday trading (together with other forms of bandwagon trading) might have caused intraday price movements to become more persistent and, hence, exploitable by technical models. As a consequence, asset price changes on the basis of daily data become bigger and more erratic which in turn causes technical trading to become less profitable on the basis of daily prices.[16]) This argument implies that the profitability of technical trading stems mainly from the importance of feed-back trading strategies (technical or others) unrelated to market fundamentals.

An evaluation of the two competing hypotheses necessitates an analysis of the profitability of technical trading on the basis of daily as well as of intraday data. A simultaneous

[16]) A careful inspection of the changes in the profitability pattern of S&P 500 trading over the subperiods provides some first evidence in favor of this hypothesis. This is so because the main reason for why the profitability has declined over time is due to changes in the ratio between the number of profitable and unprofitable positions. This ratio has continuously declined from 0.78 (1960/71) to 0.45 (1992/2000) mainly as a consequence of increasingly erratic fluctuations of daily stock prices. At the same time the typical pattern of technical trading has remained the same which implies that daily stock prices continue to follow a non-random walk.

decline of the profitability of both, interday as well as and intraday trading, would lend support to the first hypothesis. By contrast, the absence of a trend of declining profitability of technical trading on the basis of intraday data would support the second hypothesis. In order to shed some light on his issue this study analyzes the performance of technical stock trading not only on the basis of daily data but also on the basis of 30-minutes-data (see section 6).

Figure 6a: Distribution of 2580 trading systems by the ratio between the number of profitable and unprofitable positions 1960-2000
S&P 500 spot market, daily data

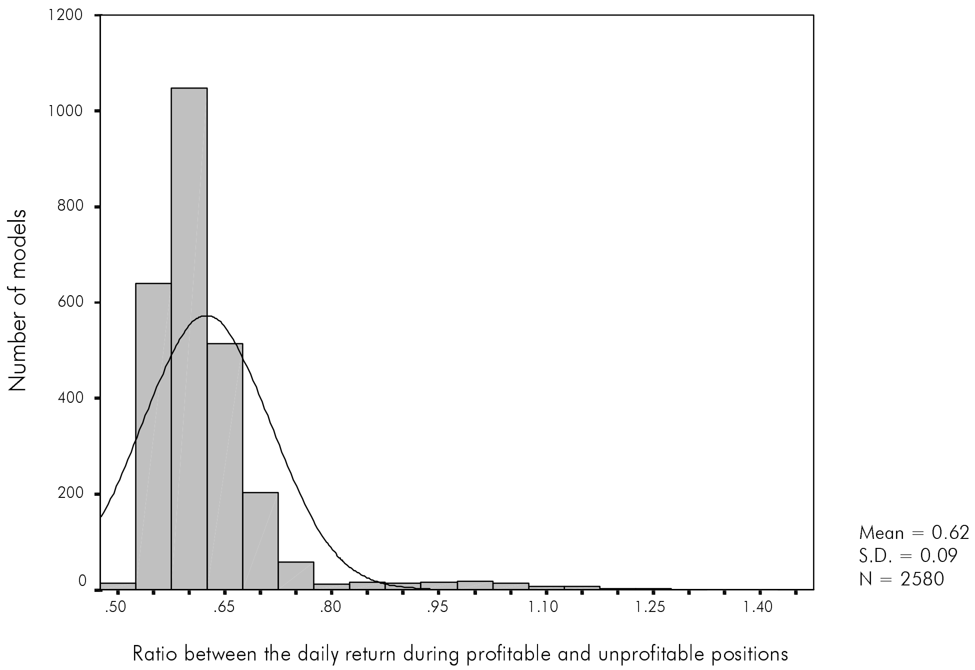


5.1.3 The pattern of profitability of the trading systems

The distribution of the 2580 trading systems by the ratios between the number of profitable and unprofitable positions, between the daily return during profitable and unprofitable positions, and between the duration of profitable and unprofitable positions is displayed in figures 6a/b to 8a/b. All three distributions are not symmetric and thus deviate from the normal distribution. The mean of the ratio between the number of profitable and unprofitable positions (S&P 500: 0.56/DAX: 0.63) as well as the mean of the ratio between the daily return during profitable and unprofitable positions (S&P 500: 0.62/DAX:

0.71) are significantly lower than 1. At the same time these ratios vary little across models (coefficient of variation amounts to roughly 0.15). These properties of the distributions of the two ratios confirm that the relative frequency of profitable and unprofitable positions as well as their average return per day do not contribute to the (ex-post) profitability of technical trading systems. In fact, these factors would have caused technical stock trading to be excessively unprofitable if the duration of profitable and unprofitable were the same.

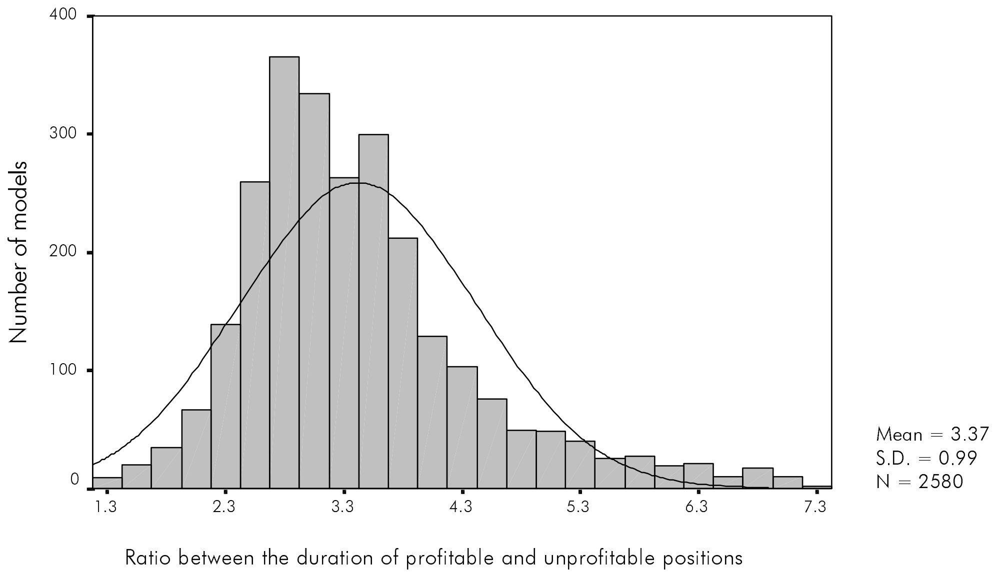
Figure 7a: Distribution of 2580 trading systems by the ratio between the daily return during profitable and unprofitable positions 1960-2000
S&P 500 spot market, daily data



However, as figures 8a/b show, profitable positions last on average 3.4 times (S&P 500) and 3.6 times (DAX) longer than unprofitable positions. At the same time the distribution of their ratio displays a much higher standard deviation relative to the mean than in the case of the ratios (NPP/NPL) and (DRP/DRL), respectively. In addition to that the distribution of the ratio between the duration of profitable and unprofitable positions is strongly skewed to the right (very high ratios - up to a value of almost 8 - occur abnormally frequently).

Figure 8a: Distribution of 2580 trading systems by the ratio between the duration of profitable and unprofitable positions 1960-2000

S&P 500 spot market, daily data



Two conclusions can be drawn from these observations. First, the profitability of technical stock trading stems exclusively from the successful exploitation of persistent price trends which is reflected by the fact that profitable positions last several times longer than unprofitable positions. Second, the high profitability of the best performing models might be the result of extraordinary high ratios between the duration of profitable and unprofitable positions which (would have) occurred only by chance (hence, the performance of these models might only be the result of "data snooping" or "model mining" by the researcher). This issue will be investigated later.

5.2 Technical stock trading in the futures markets

5.2.1 *Overview of the performance of 2580 trading systems*

Tables 10a and 10b show how the same 18 trading systems as in tables 7a/b perform in the S&P 500 futures market (1983/2000) and in the DAX futures market (1992/2000), respectively. The profitability of these models is much lower (in fact mostly negative) when trading stock index futures over the period 1983/2000 (S&P 500) and 1992/2000 (DAX) as compared to trading in the spot markets over the period 1960/2000. There are two reasons for this difference. First, the profitability of technical stock trading based on daily data has declined over the long run. Second, the return from trading or holding stock index futures is lower than trading or holding stocks in the spot markets as long as the dividend yield is lower than the market rate of interest (this has been the case over the past 20 years). This is so because the price of any futures contract rises by this difference less than the underlying stock index.

In contrast to technical stock trading in the spot markets between 1960 and 2000 no clear relationship between the average duration of profitable positions and the performance of technical models can be observed in the case of technical stock futures trading between 1983 and 2000 (S&P 500) or 1992/2000 (DAX), respectively (compare tables 7a/b to tables 10a/b).

The 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 (figure 9a). As a consequence also their t-statistics are in most cases negative (figure 10a). When trading DAX futures between 1992 and 2000 the models perform somewhat better. They produce a rate of return of 4,2% on average, their average t-statistics are in most cases positive and amount to 0.55 on average (figures 9b and 10b).

5.2.2 The performance by different types of models and trading rules

The classification of technical trading in the S&P 500 futures market between 1983 and 2000 by type of model and by type of trading rule does not display any significant difference (table 11a). However, when trading DAX futures between 1992 and 2000, the RSIN models perform much worse than the two other types of models (table 11b). The same holds true – though to a lesser extent – for the contrarian rules SG 4 to SG 6 as compared to the trend-following rules SG 1 to SG 3.

There is also no significant difference in the – on average unprofitable – performance of technical models in the S&P 500 futures market between the subperiods 1983/91 and 1992/2000 (table 12a). By contrast, in the DAX futures market the performance of the 2580 models differ between the subperiods 1992/94, 1995/97 and 1998/2000 (table 12b). However, there prevails no clear trend of the average gross rate of return across these – relatively short – subperiods.

Table 10a: Pattern of technical trading in the S&P 500 futures market, daily data, 1983-2000

		SG1	SG2[1])	SG3[1])	SG4[1])	SG5[1])	SG6[2])
Moving average models	MAS	1	2	1	12	5	1
	MAL	6	5	12	40	35	20
Gross rate of return		– 9.2	– 6.3	– 10.6	– 1.8	– 6.4	– 11.0
Sum of profits		34.5	27.5	23.9	14.6	14.3	21.5
Profitable positions							
Number		20.7	15.7	11.3	3.1	3.6	10.6
Average return							
Per position		1.7	1.8	2.1	4.8	4.0	2.0
Per day		0.15	0.16	0.13	0.07	0.07	0.10
Average duration in days		11.0	10.7	16.1	69.6	54.2	20.5
Sum of losses		– 43.7	– 33.8	– 34.4	– 16.4	– 20.7	– 32.5
Unprofitable positions							
Number		39.6	28.2	30.8	5.9	9.6	30.8
Average return							
Per position		– 1.1	– 1.2	– 1.1	– 2.8	– 2.2	– 1.1
Per day		– 0.32	– 0.26	– 0.28	– 0.11	– 0.14	– 0.24
Average duration in days		3.5	4.6	4.1	25.9	15.6	4.4
Single rates of return							
Mean		– 0.15	– 0.15	– 0.25	– 0.20	– 0.49	– 0.27
t-statistic		– 2.57	– 1.86	– 3.25	– 0.50	– 1.91	– 3.30
Median		– 0.44	– 0.44	– 0.60	– 1.42	– 1.10	– 0.51
Standard deviation		1.95	2.18	2.13	4.96	3.91	2.19
Skewness		2.87	3.87	3.13	1.64	1.84	3.48
Excess kurtosis		25.93	40.30	19.24	3.64	6.44	23.89
Sample size		1,085	789	759	161	237	745
Momentum models (time span)		5	18	13	3	35	28
Gross rate of return		– 8.4	– 3.9	– 3.1	– 5.3	– 4.5	– 1.1
Sum of profits		31.9	21.0	25.4	43.5	17.0	21.2
Profitable positions							
Number		17.2	9.2	12.2	30.9	7.8	10.0
Average return							
Per position		1.9	2.3	2.1	1.4	2.2	2.1
Per day		0.15	0.09	0.12	0.20	0.08	0.09
Average duration in days		12.3	24.7	17.6	7.2	27.6	23.2
Sum of losses		– 40.4	– 24.9	– 28.5	– 48.8	– 21.5	– 22.4
Unprofitable positions							
Number		34.3	17.6	21.9	49.2	16.8	17.9
Average return							
Per position		– 1.2	– 1.4	– 1.3	– 1.0	– 1.3	– 1.3
Per day		– 0.26	– 0.20	– 0.24	– 0.34	– 0.16	– 0.18
Average duration in days		4.5	7.1	5.5	2.9	8.2	7.1
Single rates of return							
Mean		– 0.16	– 0.15	– 0.09	– 0.07	– 0.18	– 0.04
t-statistic		– 2.32	– 1.13	– 0.89	– 1.40	– 1.32	– 0.31
Median		– 0.42	– 0.57	– 0.44	– 0.25	– 0.47	– 0.34
Standard deviation		2.15	2.85	2.50	1.78	2.89	2.94
Skewness		2.68	3.00	2.15	2.61	3.77	3.84
Excess kurtosis		21.10	16.96	9.53	29.22	26.20	24.34
Sample size		927	482	613	1,441	444	502
		SG4[1])	SG5[1])	SG6[2])	SG4[3])	SG5[3])	SG6[4])
Relative strength models (time span)		13	14	28	9	26	11
Gross rate of return		– 0.2	– 1.5	– 7.3	– 1.1	– 5.2	– 1.0
Sum of profits		29.7	21.6	14.5	30.4	10.5	27.3
Profitable positions							
Number		13.7	12.9	6.6	16.0	5.3	13.6
Average return							
Per position		2.2	1.7	2.2	1.9	2.0	2.0
Per day		0.13	0.16	0.10	0.15	0.14	0.16
Average duration in days		16.4	10.5	21.3	13.1	14.7	12.6
Sum of losses		– 30.0	– 23.0	– 21.7	– 31.4	– 15.6	– 28.3
Unprofitable positions							
Number		20.9	20.2	14.1	22.0	12.1	21.0
Average return							
Per position		– 1.4	– 1.1	– 1.5	– 1.4	– 1.3	– 1.3
Per day		– 0.21	– 0.27	– 0.16	– 0.20	– 0.19	– 0.24
Average duration in days		6.8	4.2	9.7	7.1	6.6	5.6
Single rates of return							
Mean		– 0.01	– 0.04	– 0.35	– 0.03	– 0.30	– 0.03
t-statistic		– 0.06	– 0.50	– 2.62	– 0.31	– 1.97	– 0.27
Median		– 0.33	– 0.30	– 0.62	– 0.31	– 0.58	– 0.36
Standard deviation		2.58	2.14	2.58	2.40	2.65	2.52
Skewness		1.61	3.35	1.58	2.06	4.08	2.51
Excess kurtosis		10.41	31.77	6.26	14.09	33.36	17.67
Sample size		622	594	372	684	311	623

[1]) UB1 = LB1 = 0.3. – [2]) UB1 = LB1 = 0.3, UB2 = LB2 = 0.15. – [3]) UB1 = LB1 = 0.4. – [4]) UB1 = LB1 = 0.4, UB2 = LB2 = 0.2.

Figure 9a: Distribution of 2580 trading systems by the gross rate of return 1983-2000
S&P 500 futures market, daily data

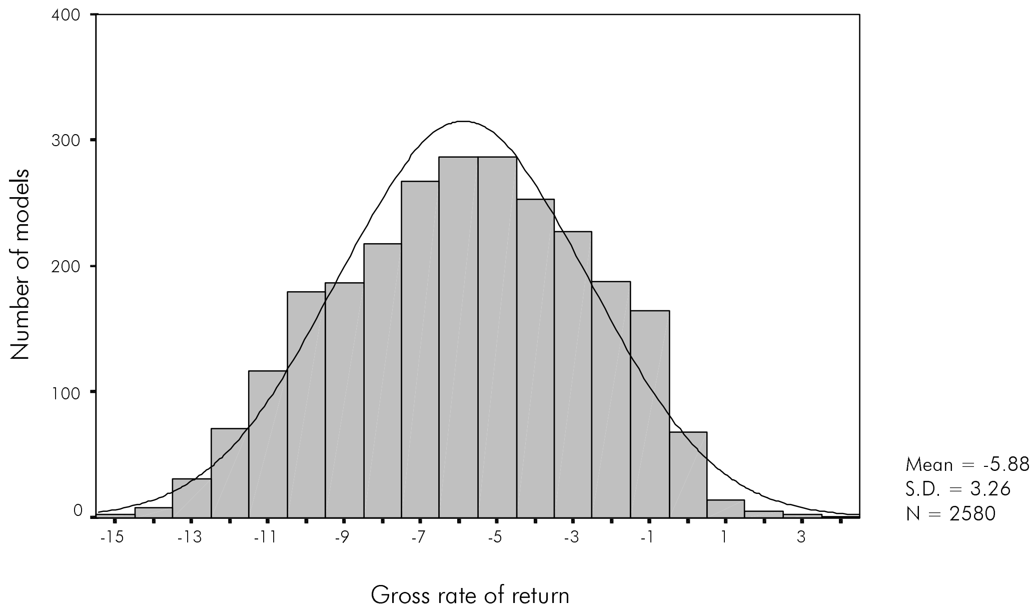


Figure 10a: Profitability and riskiness of 2580 technical trading systems 1983-2000
S&P 500 futures market, daily data

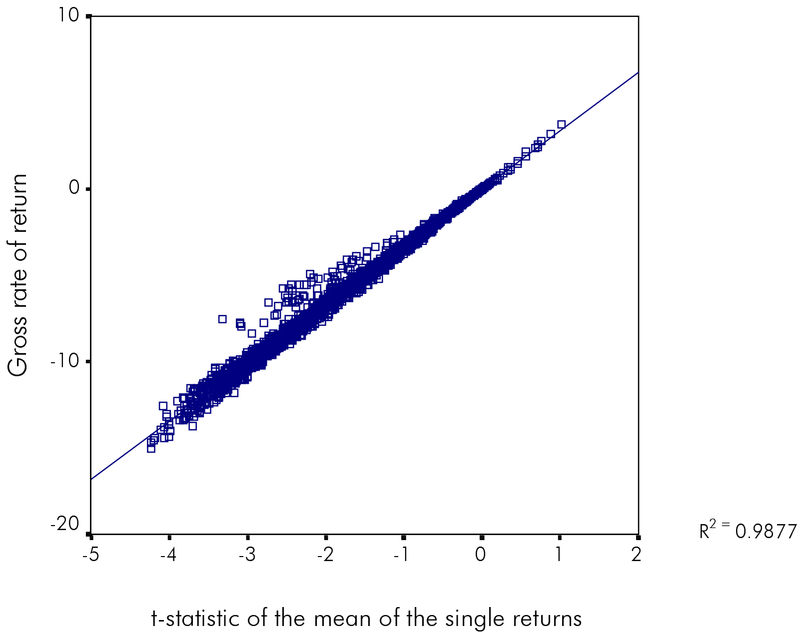


Table 11a: Components of the profitability of technical trading by types of models
S & P 500 futures market,daily data, 1983-2000

Signal genera-tion	Profitable models	Models	Share of profitable models	Gross rate of return	t-statistic	Mean and standard deviation[17]) for each class of models					
						Profitable positions			Unprofitable positions		
						Number	Return per day	Duration in days	Number	Return per day	Duration in days
Moving average models											
SG 1	10	354	2.8	– 6.0	– 1.75	5.2	0.08	47.7	12.6	– 0.15	15.2
				(3.5)	*(0.99)*	*(2.6)*	*(0.02)*	*(17.3)*	*(6.5)*	*(0.04)*	*(6.4)*
SG 2	10	354	2.8	– 5.6	– 1.68	4.4	0.08	50.2	10.4	– 0.15	16.9
				(3.4)	*(0.99)*	*(2.0)*	*(0.02)*	*(17.8)*	*(5.1)*	*(0.04)*	*(6.8)*
SG 3	2	354	0.6	– 5.8	– 1.78	5.1	0.09	40.4	12.1	– 0.16	13.5
				(3.2)	*(0.97)*	*(2.5)*	*(0.02)*	*(15.9)*	*(6.2)*	*(0.04)*	*(5.7)*
SG 4	3	354	0.8	– 6.2	– 1.80	6.6	0.09	39.0	14.9	– 0.16	12.9
				(3.3)	*(0.96)*	*(3.6)*	*(0.02)*	*(15.5)*	*(7.7)*	*(0.04)*	*(5.5)*
SG 5	3	354	0.8	– 6.1	– 1.84	5.9	0.09	39.3	13.8	– 0.17	12.7
				(3.3)	*(0.99)*	*(3.0)*	*(0.02)*	*(15.7)*	*(7.2)*	*(0.04)*	*(5.5)*
SG 6	1	354	0.3	– 6.2	– 1.84	6.3	0.09	39.0	14.4	– 0.16	12.7
				(3.3)	*(0.96)*	*(3.3)*	*(0.02)*	*(15.5)*	*(7.5)*	*(0.04)*	*(5.4)*
Total	29	2124	1.4	– 6.0	– 1.78	5.6	0.09	42.6	13.0	– 0.16	14.0
				(3.3)	*(0.98)*	*(3.0)*	*(0.02)*	*(16.9)*	*(6.9)*	*(0.04)*	*(6.1)*
Momentum models											
SG 1	0	38	0.0	– 5.9	– 1.64	10.1	0.10	24.9	20.8	– 0.19	7.5
				(3.0)	*(0.86)*	*(4.0)*	*(0.03)*	*(8.2)*	*(7.3)*	*(0.04)*	*(1.8)*
SG 2	0	38	0.0	– 5.9	– 1.68	8.6	0.10	28.2	18.2	– 0.19	8.4
				(2.9)	*(0.83)*	*(3.5)*	*(0.03)*	*(9.8)*	*(6.7)*	*(0.04)*	*(2.1)*
SG 3	0	38	0.0	– 6.0	– 1.74	10.3	0.10	23.1	20.6	– 0.21	6.9
				(2.8)	*(0.83)*	*(4.3)*	*(0.03)*	*(8.2)*	*(7.0)*	*(0.05)*	*(1.8)*
SG 4	0	38	0.0	– 6.1	– 1.70	13.1	0.11	19.4	25.1	– 0.21	6.0
				(3.0)	*(0.84)*	*(5.2)*	*(0.03)*	*(6.2)*	*(8.4)*	*(0.05)*	*(1.5)*
SG 5	0	38	0.0	– 6.0	– 1.71	11.8	0.11	20.9	22.8	– 0.21	6.4
				(2.9)	*(0.86)*	*(4.8)*	*(0.03)*	*(7.1)*	*(7.7)*	*(0.05)*	*(1.6)*
SG 6	0	38	0.0	– 6.0	– 1.71	12.5	0.11	20.0	24.0	– 0.21	6.1
				(3.0)	*(0.86)*	*(5.1)*	*(0.03)*	*(6.6)*	*(8.1)*	*(0.05)*	*(1.6)*
Total	0	228	0.0	– 6.0	– 1.69	11.1	0.10	22.7	21.9	– 0.20	6.9
				(2.9)	*(0.84)*	*(4.7)*	*(0.03)*	*(8.3)*	*(7.8)*	*(0.04)*	*(1.9)*
Relative strength models											
SG 4	10	76	13.2	– 3.9	– 1.13	9.6	0.11	34.8	15.7	– 0.15	22.8
				(3.3)	*(0.97)*	*(8.4)*	*(0.04)*	*(26.5)*	*(11.2)*	*(0.08)*	*(24.9)*
SG 5	1	76	1.3	– 5.0	– 1.85	10.0	0.15	12.4	18.1	– 0.24	5.6
				(2.1)	*(0.76)*	*(6.3)*	*(0.02)*	*(3.3)*	*(9.2)*	*(0.06)*	*(1.9)*
SG 6	2	76	2.6	– 5.1	– 1.61	10.1	0.13	21.6	18.1	– 0.19	10.0
				(2.4)	*(0.80)*	*(7.4)*	*(0.03)*	*(12.6)*	*(10.0)*	*(0.08)*	*(5.4)*
Total	13	228		*2.70*	*0.898*	*7.4*	*0.04*	*19.3*	*10.2*	*0.08*	*16.4*
				(– 4.7)	*(– 1.53)*	*(9.9)*	*(0.13)*	*(22.9)*	*(17.3)*	*(– 0.19)*	*(12.8)*
All models				*2.70*	*0.898*	*7.4*	*0.04*	*19.3*	*10.2*	*0.08*	*16.4*
SG 1	10	392	2.6	– 6.0	– 1.74	5.7	0.08	45.5	13.4	– 0.15	14.4
				(3.4)	*(0.98)*	*(3.1)*	*(0.02)*	*(17.9)*	*(7.0)*	*(0.04)*	*(6.5)*
SG 2	10	392	2.6	– 5.7	– 1.68	4.8	0.09	48.1	11.1	– 0.15	16.1
				(3.3)	*(0.98)*	*(2.5)*	*(0.02)*	*(18.4)*	*(5.8)*	*(0.04)*	*(6.9)*
SG 3	2	392	0.5	– 5.8	– 1.77	5.6	0.09	38.8	12.9	– 0.17	12.8
				(3.1)	*(0.96)*	*(3.1)*	*(0.02)*	*(16.2)*	*(6.8)*	*(0.05)*	*(5.8)*
SG 4	13	468	2.8	– 5.8	– 1.69	7.6	0.09	36.7	15.8	– 0.16	13.9
				(3.4)	*(0.98)*	*(5.2)*	*(0.03)*	*(18.0)*	*(8.9)*	*(0.05)*	*(11.9)*
SG 5	4	468	0.9	– 5.9	– 1.83	7.0	0.10	33.4	15.2	– 0.18	11.0
				(3.1)	*(0.94)*	*(4.4)*	*(0.03)*	*(17.4)*	*(8.1)*	*(0.06)*	*(5.7)*
SG 6	3	468	0.6	– 6.0	– 1.79	7.4	0.10	34.6	15.8	– 0.17	11.7
				(3.2)	*(0.93)*	*(4.8)*	*(0.03)*	*(16.4)*	*(8.4)*	*(0.05)*	*(5.6)*
Total	42	2580	1.6	– 5.9	– 1.75	6.5	0.09	39.1	14.2	– 0.17	13.2
				(3.3)	*(0.96)*	*(4.2)*	*(0.03)*	*(18.2)*	*(7.8)*	*(0.05)*	*(7.7)*

[17]) In parentheses.

Table 12a: Components of 2,580 trading system by classes of the t-statistic and subperiods
S & P 500 futures market, daily data, 1983-2000

t-statistic of the mean of the single returns	Number of models	Relative share in %	Gross rate of return	t-statistic	Mean for each class of models					
					Profitable positions			Unprofitable positions		
					Number	Return per day	Duration in days	Number	Return per day	Duration in days
1983-1991										
<0	2,411	93.4	– 5.5	– 1.06	6.3	0.11	39.5	14.1	– 0.17	13.7
0-<1	164	6.4	1.3	0.23	7.8	0.11	37.2	12.7	– 0.16	13.8
1-<2	5	0.2	6.7	1.20	13.0	0.15	17.7	17.6	– 0.19	8.1
Total	2,580	100.0	– 5.1	– 0.97	6.4	0.11	39.3	14.0	– 0.17	13.7
1992-2000										
<0	2,486	96.4	– 7.0	– 1.66	6.6	0.08	38.3	14.7	– 0.16	12.8
0-<1	94	3.6	0.8	0.19	5.6	0.08	46.2	7.9	– 0.12	19.1
1-<2										
Total	2,580	100.0	– 6.7	– 1.59	6.5	0.08	38.6	14.4	– 0.16	13.0
1983-2000										
<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
Total	2,580	100.0	– 5.9	– 1.75	6.5	0.09	39.1	14.2	– 0.17	13.2

5.2.3 The pattern of profitability of the trading systems

Even though technical models perform poorly in the stock index futures markets based on daily data they display the same pattern of (mostly negative) profitability as in the spot markets (figures 11a/b to 13a/b). The number of unprofitable positions is by roughly 50% smaller than the number of profitable positions, the average return per day (in absolute terms) during unprofitable positions is by roughly 40% lower than during profitable positions, however, the average duration of profitable positions lasts 3.1 times (S&P 500) and 3.6 times (DAX) longer than the duration of unprofitable positions.

This pattern implies that "underlying" price trends occur also in the stock index futures markets more frequently than could be expected if daily stock prices followed 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.

Figure 11a: Distribution of 2580 trading systems by the ratio between the number of profitable and unprofitable positions 1983-2000
S&P 500 futures market, daily data

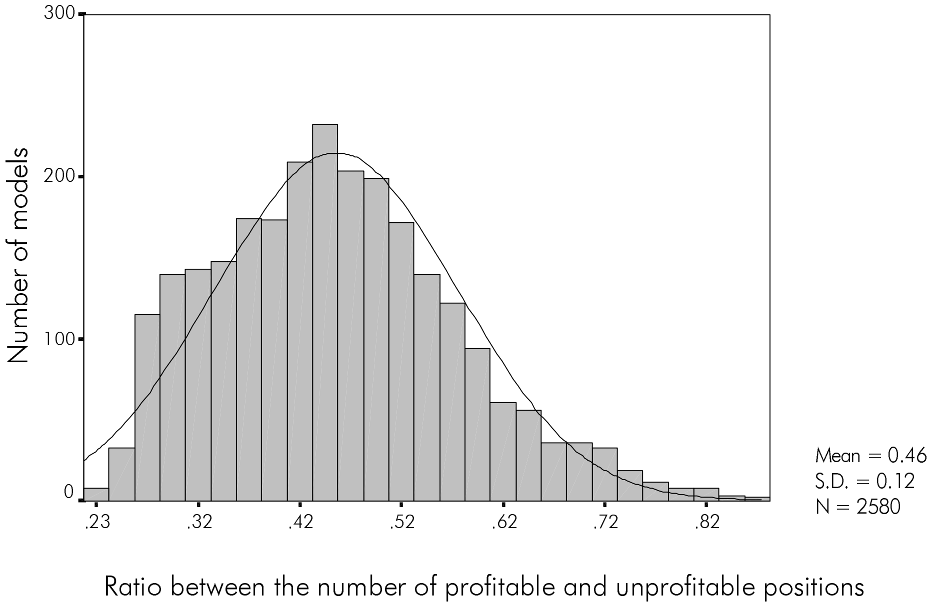


Figure 12a: Distribution of 2580 trading systems by the ratio between the daily return during profitable and unprofitable positions 1983-2000
S&P 500 futures market, daily data

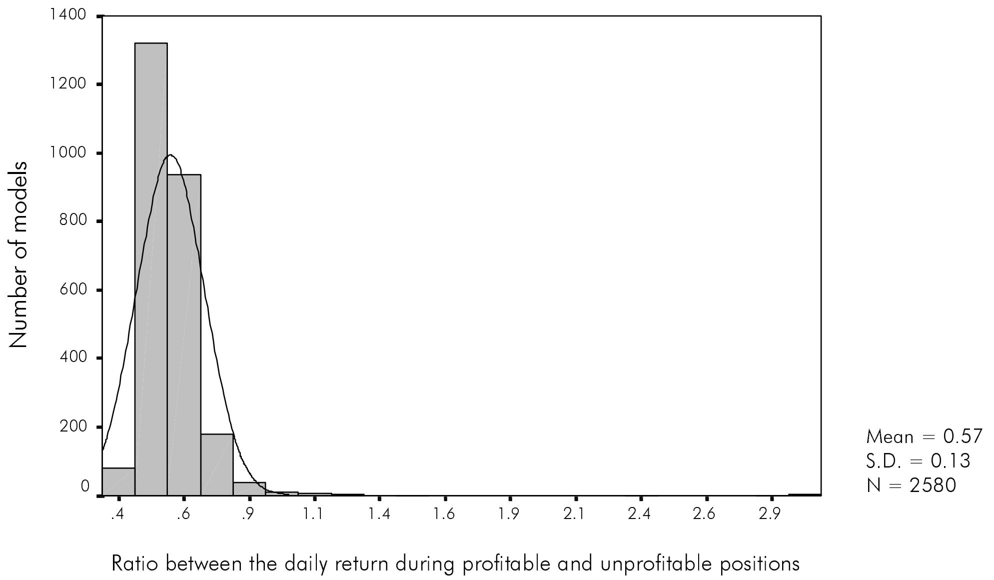
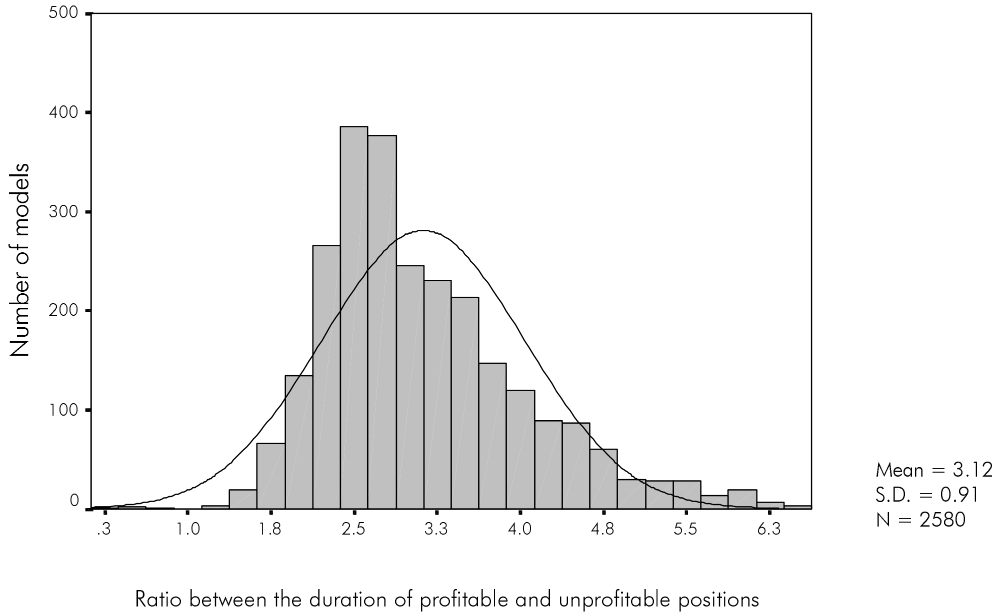


Figure 13a: Distribution of 2580 trading systems by the ratio between the duration of profitable and unprofitable positions 1983-2000
S&P 500 futures market, daily data



5.3 Comparison of technical stock trading between the spot markets and the futures markets

Tables 13a and 13b compare the performance of the 2580 technical models over the same sample period between the spot market and the futures market. The overall profitability - which is negative in the case of S&P 500 futures trading - is by almost 4 percentage points lower when futures contracts are traded as compared to trading the "underlying" stocks in the spot market (this holds true for both markets, the S&P 500 as well as the DAX futures market). This difference is roughly equal to he difference between the average dividend yield of the 500 (30) stocks included in the S&P 500 (DAX) index (by this difference do futures prices rise less strongly than spot prices).

The pattern of profitability of the 2580 models does not differ between trading futures contracts and trading the "underlying" stocks in the spot market. This is so because arbitrage between the spot market and the futures market through "program trading" ensures that stock prices move in an "synchronised" manner.

Table 13a: Pattern of profitability of 2,580 trading systems by classes of the t-statistic
Comparison between trading in the S & P 500 spot and futures market 1983-2000

t-statistic of the mean of the single returns	Number of models	Relative share in %	Gross rate of return	t-statistic	Mean and standard deviation[18]) for each class of models					
					Profitable positions			Unprofitable positions		
					Number	Return per day	Duration in days	Number	Return per day	Duration in days
Spot market										
<0	2,065	80.0	– 3.6	– 1.05	5.8	0.09	40.9	13.1	– 0.16	13.0
			(2.2)	*(0.67)*	*(2.9)*	*(0.02)*	*(16.4)*	*(5.8)*	*(0.03)*	*(6.0)*
0-<1	462	17.9	1.2	0.35	7.8	0.10	41.6	13.6	– 0.15	14.4
			(0.9)	*(0.25)*	*(5.8)*	*(0.03)*	*(24.5)*	*(9.3)*	*(0.05)*	*(8.5)*
1-<2	49	1.9	4.5	1.32	16.2	0.14	15.2	24.4	– 0.21	5.8
			(1.0)	*(0.27)*	*(5.6)*	*(0.03)*	*(8.5)*	*(8.6)*	*(0.04)*	*(3.2)*
2-<3.0	4	0.2	8.2	2.40	26.0	0.18	8.8	38.4	– 0.27	3.1
			(0.7)	*(0.19)*	*(1.8)*	*(0.01)*	*(0.6)*	*(1.6)*	*(0.01)*	*(0.1)*
Total	2,580	100.0	– 2.6	– 0.75	6.4	0.10	40.5	13.4	– 0.16	13.1
			(3.0)	*(0.87)*	*(4.1)*	*(0.02)*	*(18.4)*	*(6.9)*	*(0.04)*	*(6.6)*
Futures market										
<0	2,537	98.3	– 6.0	– 1.78	6.4	0.09	39.2	14.2	– 0.17	13.2
			(3.2)	*(0.93)*	*(4.2)*	*(0.03)*	*(18.1)*	*(7.8)*	*(0.05)*	*(7.6)*
0-<1	42	1.6	0.8	0.24	7.6	0.11	36.2	11.0	– 0.15	15.9
			(0.9)	*(0.24)*	*(5.3)*	*(0.03)*	*(22.5)*	*(6.7)*	*(0.05)*	*(7.8)*
1-<2	1	0.0	3.7	1.02	10.2	0.14	20.2	15.8	– 0.15	10.1
			-	-	-	-	-	-	-	-
2-<3.0	-	-	-	-	-	-	-	-	-	-
			-	-	-	-	-	-	-	-
Total	2,580	100.0	– 5.9	– 1.75	6.5	0.09	39.1	14.2	– 0.17	13.2
			(3.3)	*(0.96)*	*(4.2)*	*(0.03)*	*(18.2)*	*(7.8)*	*(0.05)*	*(7.7)*

5.4 Comparison of technical stock trading between the S&P 500 and the DAX futures markets

Table 14 compares the performance of the 2580 models over the same sample period (1992/2000) between the S&P 500 futures market and the DAX futures market. Whereas the models produce a slightly positive gross rate of return when trading DAX futures contracts (4.2%), they produce a significant loss of 6.7% per year in the S&P 500 futures market. This difference is primarily due to the fact that the ratio between the number of profitable and unprofitable positions as well as the ratio between the average return per day during profitable and unprofitable positions is significantly lower in the S&P 500 futures market as compared to the DAX futures market. This different pattern of profitability can most plausibly be explained by daily stock price fluctuations being more erratic in the

[18]) In parentheses.

S&P 500 futures market as compared to the DAX futures market. The difference in the volatility of daily stock prices between the two markets could be caused in two different ways (these hypothetical explanations are similar to those which might also explain the decline in the profitability of technical trading based on daily data over time – see section 5.1.2).

Table 14: Pattern of profitability of 2,580 trading systems by classes of the t-statistic
Comparison between the S & P 500 and the DAX futures market, daily data, 1992-2000

t-statistic of the mean of the single returns	Number of models	Relative share in %	Gross rate of return	Mean and standard deviation[19]) for each class of models						
				t-statistic	Profitable positions			Unprofitable positions		
					Number	Return per day	Duration in days	Number	Return per day	Duration in days
S & P 500										
<0	2,486	96.4	– 7.0	– 1.66	6.6	0.08	38.3	14.7	– 0.16	12.8
			(4.0)	*(0.99)*	*(4.3)*	*(0.02)*	*(18.1)*	*(8.1)*	*(0.05)*	*(7.6)*
0-<1	94	3.6	0.8	0.19	5.6	0.08	46.2	7.9	– 0.12	19.1
			(0.8)	*(0.19)*	*(3.9)*	*(0.02)*	*(18.6)*	*(4.6)*	*(0.04)*	*(6.4)*
1-<2	–	–	–	–	–	–	–	–	–	–
			–	–	–	–	–	–	–	–
Total	2,580	100.0	– 6.7	– 1.59	6.5	0.08	38.6	14.4	– 0.16	13.0
			(4.2)	*(1.03)*	*(4.3)*	*(0.02)*	*(18.2)*	*(8.1)*	*(0.05)*	*(7.6)*
DAX										
<0	384	14.9	– 5.2	– 0.92	9.2	0.15	25.0	16.8	– 0.26	10.4
			(4.3)	*(0.75)*	*(4.9)*	*(0.04)*	*(17.0)*	*(7.6)*	*(0.08)*	*(11.3)*
0-<1	1,494	57.9	4.4	0.61	6.0	0.12	49.4	11.5	– 0.20	14.2
			(2.0)	*(0.26)*	*(4.0)*	*(0.03)*	*(20.6)*	*(7.0)*	*(0.06)*	*(7.6)*
1-<2	702	27.2	8.9	1.21	6.0	0.12	44.4	9.9	– 0.18	13.6
			(1.3)	*(0.16)*	*(3.2)*	*(0.02)*	*(12.2)*	*(5.4)*	*(0.05)*	*(4.9)*
Total	2,580	100.0	4.2	0.55	6.5	0.13	44.4	11.8	– 0.20	13.5
			(5.0)	*(0.76)*	*(4.1)*	*(0.03)*	*(20.0)*	*(7.0)*	*(0.07)*	*(7.8)*

In the first case one would argue that the new information and communication technologies have rendered stock exchanges in the U.S. more efficient than in Germany since these technologies have generally been adopted to a greater extent in the U.S. than in Germany. In the second case one would argue that the new technologies induced more traders in the U.S. as compared to Germany to switch from trading based on daily data to trading based on intraday data. As a consequence intraday price movements might have become more persistent and, hence, more exploitable in U.S. markets as compared to German markets.

[19]) In parentheses.

In order to evaluate these two competing hypotheses the performance of technical models based on 30-minutes-data has been analysed for both markets, the S&P 500 futures market as well as the DAX futures market.

6. The performance of technical trading systems based on 30-minutes-futures-prices over the whole sample period

This section investigates the performance of the 2580 trading systems on the basis of 30-minutes-data in the S&P 500 futures market as well as in the DAX futures market.

6.1 Overview of the performance of 2580 trading systems

Tables 15a and 15b display the performance of the same 18 technical models as in tables 10a/b using 30-minutes-prices instead of daily prices. Several interesting observations can be drawn from a comparison between tables 15a/b and tables 10a/b. First, the profitability of each model is significantly higher when trading on the basis of 30-minutes-data as compared to daily data. In the S&P 500 futures market most models produce an gross rate of return of more than 10% per year between 1983 and 2000, 5 models realize even an gross return of more than 20% per year. When trading DAX futures contracts on the basis of 30-minutes-prices the profitability is even higher. 12 out of 18 models produce an gross rate of return in excess of 20% per year between 1997 and 2000, in 3 cases the annual profitability is even higher than 50% per year. Second, the gross rate of return of the models tends to be the higher the shorter is the average duration of their profitable positions. In the case of the best performing models, e. g., the duration of profitable positions last on average less than 1 day (this observation hold true for trading S&P 500 as well as DAX futures contracts). Third, the means of the single rates of return is in most cases significantly higher than zero (the t-statistic mostly exceeds 2.5), hence, the probability of making an overall loss when blindly following one of these trading systems is close to zero.

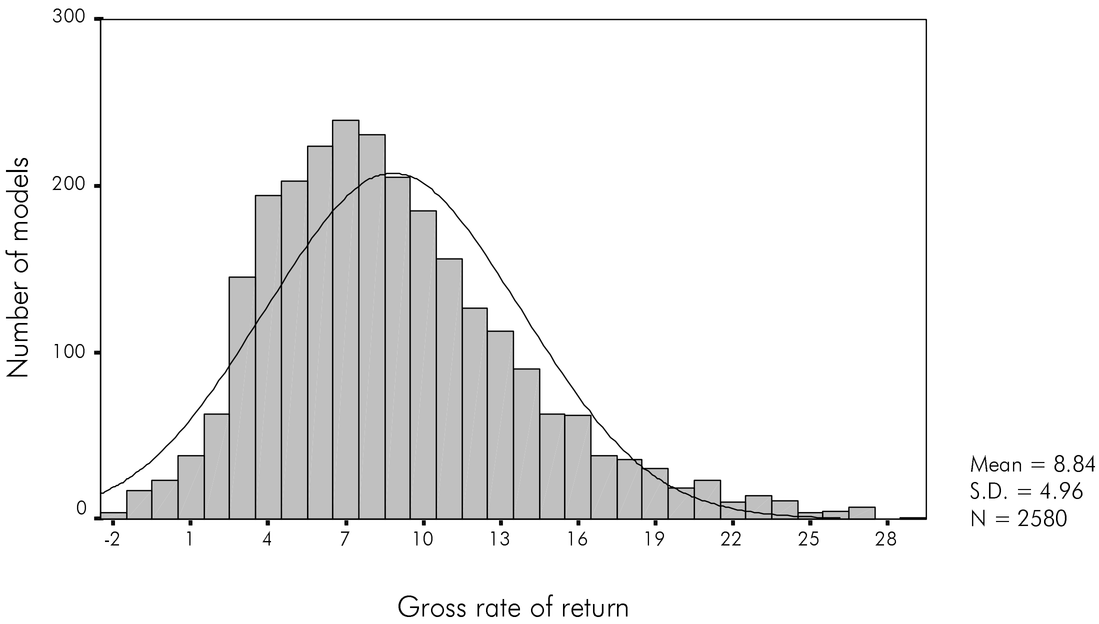
Table 15a: Pattern of technical trading in the S&P 500 futures market, 30-minutes-data, 1983-2000

		SG1	SG2[1])	SG3[1])	SG4[1])	SG5[1])	SG6[2])
Moving average models	MAS	1	2	1	12	5	1
	MAL	6	5	12	40	35	20
Gross rate of return		20.5	7.2	15.9	5.7	8.7	13.9
Sum of profits		145.6	45.0	74.6	58.7	58.1	103.2
Profitable positions							
Number		265.9	68.0	133.0	50.4	59.8	169.3
Average return							
Per position		0.6	0.7	0.6	1.2	1.0	0.6
Per day		0.65	0.89	0.77	0.25	0.32	0.50
Average duration in days		0.8	0.7	0.7	4.6	3.1	1.2
Sum of losses		– 125.0	– 37.7	– 58.8	– 53.0	– 49.4	– 89.3
Unprofitable positions							
Number		554.9	88.8	226.2	64.6	103.8	315.2
Average return							
Per position		– 0.2	– 0.4	– 0.3	– 0.8	– 0.5	– 0.3
Per day		– 0.88	– 1.18	– 1.17	– 0.41	– 0.50	– 0.83
Average duration in days		0.3	0.4	0.2	2.0	1.0	0.3
Single rates of return							
Mean		0.03	0.05	0.04	0.05	0.05	0.03
t-statistic		4.75	2.25	4.45	1.59	2.63	3.41
Median		– 0.10	– 0.08	– 0.08	– 0.13	– 0.18	– 0.11
Standard deviation		0.64	1.09	0.80	1.42	1.09	0.79
Skewness		1.72	– 1.80	– 0.30	1.98	4.33	2.73
Excess kurtosis		206.10	143.98	223.01	17.42	55.40	242.64
Sample size		14,774	2,822	6,465	2,070	2,944	8,722
Momentum models (time span)		5	18	13	3	35	28
Gross rate of return		14.3	1.3	17.4	4.6	5.1	13.9
Sum of profits		134.9	67.0	80.9	154.5	65.7	80.9
Profitable positions							
Number		247.8	67.9	148.3	356.4	110.9	143.3
Average return							
Per position		0.5	1.0	0.6	0.4	0.6	0.6
Per day		0.61	0.35	0.49	0.74	0.30	0.34
Average duration in days		0.9	2.9	1.1	0.6	2.0	1.7
Sum of losses		– 120.6	– 65.7	– 63.4	– 149.8	– 60.6	– 67.0
Unprofitable positions							
Number		458.8	133.0	215.4	428.2	192.1	227.1
Average return							
Per position		– 0.3	– 0.5	– 0.3	– 0.4	– 0.3	– 0.3
Per day		– 0.83	– 0.54	– 0.86	– 0.97	– 0.61	– 0.66
Average duration in days		0.3	0.9	0.3	0.4	0.5	0.5
Single rates of return							
Mean		0.02	0.01	0.05	0.01	0.02	0.04
t-statistic		3.18	0.35	4.68	1.13	1.39	3.91
Median		– 0.09	– 0.19	– 0.06	– 0.06	– 0.09	– 0.08
Standard deviation		0.72	1.13	0.83	0.62	0.89	0.78
Skewness		0.67	2.68	4.76	– 3.62	– 1.15	4.19
Excess kurtosis		240.76	67.61	286.62	187.78	134.59	59.04
Sample size		12,718	3,616	6,547	14,122	5,454	6,667
		SG4[1])	SG5[1])	SG6[2])	SG4[3])	SG5[3])	SG6[4])
Relative strength models (time span)		13	14	28	9	26	11
Gross rate of return		27.1	20.5	12.4	23.3	10.2	23.6
Sum of profits		120.6	86.0	74.4	131.6	55.6	111.0
Profitable positions							
Number		207.3	178.8	102.1	232.8	85.6	196.7
Average return							
Per position		0.6	0.5	0.7	0.6	0.7	0.6
Per day		0.52	0.54	0.43	0.61	0.51	0.63
Average duration in days		1.1	0.9	1.7	0.9	1.3	0.9
Sum of losses		– 93.5	– 65.5	– 62.0	– 108.3	– 45.4	– 87.5
Unprofitable positions							
Number		272.0	251.9	163.7	310.6	136.7	278.3
Average return							
Per position		– 0.3	– 0.3	– 0.4	– 0.4	– 0.3	– 0.3
Per day		– 0.71	– 0.86	– 0.57	– 0.73	– 0.68	– 0.75
Average duration in days		0.5	0.3	0.7	0.5	0.5	0.4
Single rates of return							
Mean		0.06	0.05	0.05	0.04	0.05	0.05
t-statistic		6.75	6.23	3.48	5.69	3.47	5.98
Median		– 0.06	– 0.06	– 0.09	– 0.06	– 0.09	– 0.07
Standard deviation		0.78	0.67	0.93	0.75	0.83	0.77
Skewness		2.41	3.83	7.18	5.20	0.30	5.89
Excess kurtosis		74.49	132.97	186.05	106.32	103.34	155.63
Sample size		8,628	7,753	4,784	9,781	4,002	8,551

[1]) UB1 = LB1 = 0.3. – [2]) UB1 = LB1 = 0.3, UB2 = LB2 = 0.15. – [3]) UB1 = LB1 = 0.4. – [4]) UB1 = LB1 = 0.4, UB2 = LB2 = 0.2.

Technical stock trading based on 30-minutes-prices displays the same pattern of profitability as observed when trading is based on daily data. The number of profitable positions is smaller than the number of unprofitable positions, the average return per 30-minutes-interval is smaller (in absolute terms) during profitable positions as cpmpared to unprofitable positions, however, profitable positions last on average 2 to 3 times longer than unprofitable positions. This pattern is reflected by the distribution of the single rates of return. The mean is higher than the median (which is always negative), the distribution is skewed to the right and extremely leptokurtotic.

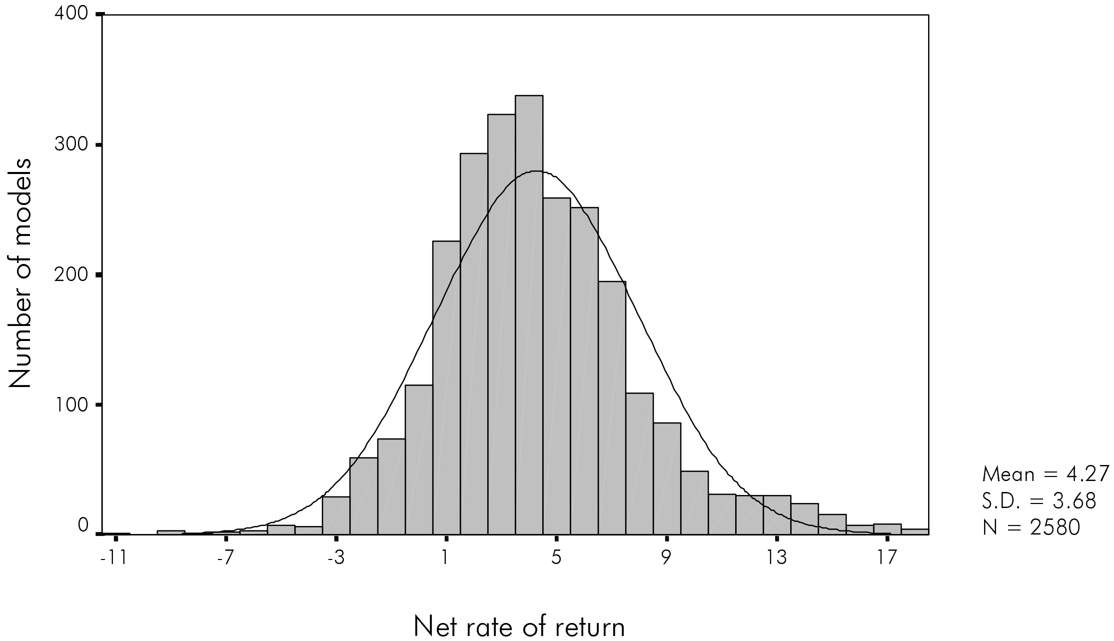
Figure 14a: Distribution of 2580 trading systems by the gross rate of return 1983-2000
S&P 500 futures market, 30 minutes data



Figures 14a/b and 15a/b 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%). The profitability of the models is much higher when trading DAX futures, they produce between 1997 and 2000 a gross and net rate of return of 23.2% and 17.1%, respectively.

The t-statistic of the mean of the single rates of return exceeds 2.0 in most cases (figures 16a/b), it amounts on average over all models to 2.4 in the case of S&P 500 futures trading, and to 2.1 in the case of DAX futures trading (tables 16a/b).

Figure 15a: Distribution of 2580 trading systems by the net rate of return 1983-2000
S&P 500 futures market, 30 minutes data



These results indicate that there was rather little risk associated with technical stock trading based on 30-minutes-data if traders had rigidly adhered to particular 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 past performance, then this system might suffer substantial losses out-of-sample if its abnormal profitability in sample occurred mainly by chance (the issue of model selection and the ex-ante performance of technical models will be investigated later).

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 so that he would omit the profits from the successful exploitation of persistent stock price trends over the long run.

Table 16a: Components of the profitability of technical trading by types of models

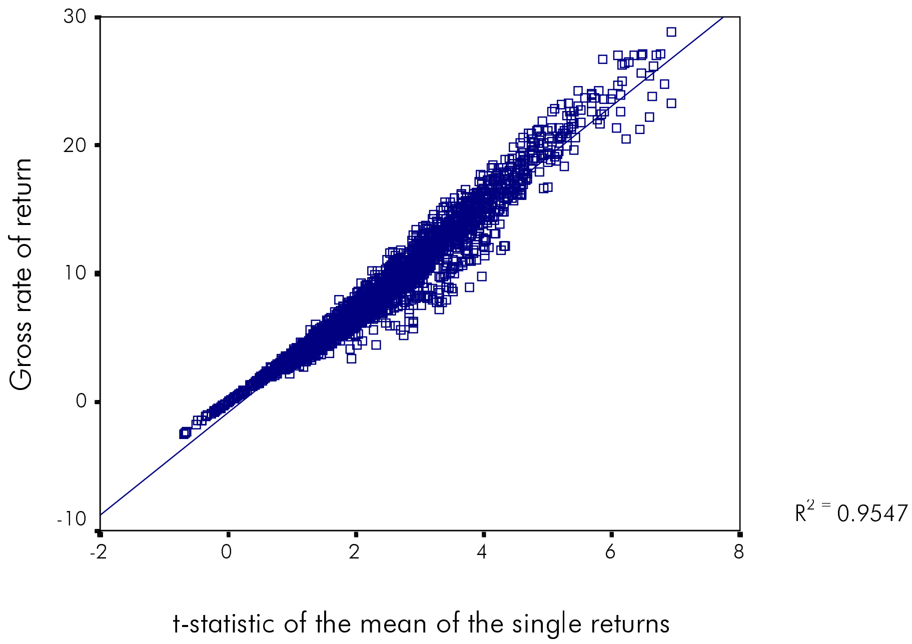
S & P 500 futures market, 30-minutes-data, 1983-2000

Signal generation	Profitable models	Number of models	Share of profitable models	Gross rate of return	Net rate of return	t-statistic	Mean and standard deviation[20] for each class of models					
							Profitable positions			Unprofitable positions		
							Number	Return per day	Duration in days	Number	Return per day	Duration in days
Moving average models												
SG 1	336	354	94.9	7.1	2.6	1.8	75.37	0.32	3.5	143.69	– 0.49	1.1
				(4.7)	*(3.1)*	*(1.1)*	*(34.71)*	*(0.07)*	*(1.2)*	*(76.04)*	*(0.10)*	*(0.5)*
SG 2	340	354	96.0	4.4	2.1	1.3	43.75	0.34	3.8	69.87	– 0.50	1.4
				(2.7)	*(2.1)*	*(0.7)*	*(14.86)*	*(0.10)*	*(1.2)*	*(24.26)*	*(0.13)*	*(0.5)*
SG 3	354	354	100.0	7.2	4.1	2.4	58.86	0.48	2.1	94.48	– 0.73	0.7
				(2.9)	*(2.1)*	*(0.9)*	*(21.92)*	*(0.19)*	*(1.0)*	*(46.91)*	*(0.26)*	*(0.4)*
SG 4	354	354	100.0	11.8	7.3	3.0	93.93	0.37	2.7	128.62	– 0.51	1.4
				(4.5)	*(3.5)*	*(1.0)*	*(39.95)*	*(0.08)*	*(0.9)*	*(70.17)*	*(0.12)*	*(0.6)*
SG 5	354	354	100.0	9.4	5.0	2.7	85.63	0.42	2.2	135.26	– 0.62	0.8
				(4.3)	*(2.9)*	*(1.1)*	*(37.07)*	*(0.12)*	*(0.9)*	*(67.37)*	*(0.14)*	*(0.3)*
SG 6	354	354	100.0	10.5	5.9	2.8	90.44	0.39	2.4	135.83	– 0.54	1.1
				(4.6)	*(3.3)*	*(1.1)*	*(39.08)*	*(0.10)*	*(0.8)*	*(69.46)*	*(0.12)*	*(0.4)*
Total	2092	2124	98.5	8.4	4.5	2.3	74.67	0.39	2.8	117.96	– 0.57	1.1
				(4.7)	*(3.4)*	*(1.2)*	*(37.27)*	*(0.13)*	*(1.2)*	*(67.16)*	*(0.17)*	*(0.5)*
Momentum models												
SG 1	38	38	100.0	9.5	2.1	2.4	128.20	0.37	2.2	238.73	– 0.59	0.6
				(4.5)	*(3.4)*	*(1.0)*	*(61.32)*	*(0.12)*	*(0.8)*	*(109.76)*	*(0.12)*	*(0.2)*
SG 2	38	38	100.0	6.9	2.6	1.8	76.62	0.37	3.0	134.72	– 0.57	0.9
				(3.9)	*(3.1)*	*(0.9)*	*(32.86)*	*(0.15)*	*(1.2)*	*(50.98)*	*(0.16)*	*(0.3)*
SG 3	38	38	100.0	8.8	2.2	2.4	125.09	0.45	1.6	199.37	– 0.77	0.5
				(3.8)	*(3.1)*	*(1.0)*	*(45.08)*	*(0.20)*	*(0.7)*	*(51.46)*	*(0.24)*	*(0.2)*
SG 4	38	38	100.0	12.5	2.5	3.1	199.07	0.44	1.3	293.77	– 0.72	0.4
				(5.1)	*(4.9)*	*(1.2)*	*(64.19)*	*(0.13)*	*(0.4)*	*(68.68)*	*(0.10)*	*(0.1)*
SG 5	38	38	100.0	11.0	2.3	2.9	169.51	0.45	1.4	264.45	– 0.76	0.4
				(4.5)	*(3.9)*	*(1.1)*	*(66.63)*	*(0.17)*	*(0.5)*	*(86.11)*	*(0.17)*	*(0.1)*
SG 6	38	38	100.0	11.8	2.3	3.0	186.42	0.44	1.3	284.58	– 0.73	0.4
				(4.8)	*(4.5)*	*(1.1)*	*(66.40)*	*(0.15)*	*(0.5)*	*(82.90)*	*(0.12)*	*(0.1)*
Total	228	228	100.0	10.1	2.3	2.6	147.49	0.42	1.8	235.94	– 0.69	0.5
				(4.8)	*(3.8)*	*(1.1)*	*(70.72)*	*(0.16)*	*(1.0)*	*(94.60)*	*(0.18)*	*(0.2)*
Relative strength models												
SG 4	75	76	98.7	12.3	4.9	3.0	148.47	0.44	2.3	217.54	– 0.56	1.1
				(6.4)	*(5.6)*	*(1.5)*	*(108.96)*	*(0.14)*	*(1.5)*	*(145.58)*	*(0.22)*	*(0.8)*
SG 5	76	76	100.0	10.8	3.4	3.3	145.96	0.55	1.1	225.65	– 0.79	0.4
				(5.1)	*(4.1)*	*(1.3)*	*(86.18)*	*(0.10)*	*(0.4)*	*(126.01)*	*(0.16)*	*(0.1)*
SG 6	76	76	100.0	11.6	3.8	3.0	150.41	0.50	1.6	233.86	– 0.65	0.7
				(6.1)	*(4.9)*	*(1.5)*	*(98.82)*	*(0.12)*	*(0.8)*	*(134.72)*	*(0.20)*	*(0.3)*
Total	227	228	99.6	11.5	4.0	3.1	148.28	0.50	1.7	225.68	– 0.66	0.7
				(5.9)	*(4.9)*	*(1.4)*	*(98.01)*	*(0.13)*	*(1.1)*	*(135.24)*	*(0.22)*	*(0.6)*
All models												
SG 1	374	392	95.4	7.3	2.6	1.9	80.49	0.32	3.4	152.90	– 0.50	1.1
				(4.8)	*(3.2)*	*(1.1)*	*(41.09)*	*(0.08)*	*(1.2)*	*(84.57)*	*(0.10)*	*(0.5)*
SG 2	378	392	96.4	4.7	2.1	1.3	46.94	0.34	3.7	76.15	– 0.51	1.4
				(2.9)	*(2.3)*	*(0.8)*	*(19.91)*	*(0.10)*	*(1.3)*	*(33.86)*	*(0.14)*	*(0.5)*
SG 3	392	392	100.0	7.3	3.9	2.4	65.28	0.47	2.0	104.64	– 0.73	0.7
				(3.0)	*(2.3)*	*(0.9)*	*(31.80)*	*(0.19)*	*(0.9)*	*(56.59)*	*(0.26)*	*(0.4)*
SG 4	467	468	99.8	12.0	6.5	3.0	111.33	0.39	2.6	156.47	– 0.54	1.2
				(4.9)	*(4.3)*	*(1.1)*	*(67.23)*	*(0.10)*	*(1.1)*	*(101.14)*	*(0.15)*	*(0.7)*
SG 5	468	468	100.0	9.8	4.5	2.8	102.24	0.44	1.9	160.43	– 0.66	0.7
				(4.5)	*(3.4)*	*(1.2)*	*(58.92)*	*(0.13)*	*(0.9)*	*(92.85)*	*(0.16)*	*(0.4)*
SG 6	468	468	100.0	10.8	5.3	2.9	107.97	0.42	2.2	163.83	– 0.58	1.0
				(4.9)	*(3.9)*	*(1.2)*	*(64.02)*	*(0.11)*	*(0.9)*	*(98.41)*	*(0.15)*	*(0.5)*
Total	2547	2580	98.7	8.8	4.3	2.4	87.61	0.40	2.6	137.90	– 0.59	1.0
				(5.0)	*(3.7)*	*(1.2)*	*(56.65)*	*(0.13)*	*(1.2)*	*(89.27)*	*(0.18)*	*(0.5)*

[20]) In parentheses.

The high gross rates of return which are at the same time significantly different from zero (as the t-statistics show) shed doubts on the hypothesis that the stock index futures markets are weakly efficient since the expected value of trading futures based only on the information contained in past prices is zero.

Figure 16a: Profitability and riskiness of 2580 technical trading systems 1983-2000
S&P 500 futures market, 30 minutes data



6.2 The performance by different types of models and trading rules

When trading S&P 500 futures based on 30-minutes-data between 1983 and 2000 the RSIN models perform best, and the moving average models perform worst. However, the differences in the average gross rates of return is rather small (the RSIN models and the momentum models produce an average GRR of 11.5% and of 10.1% per year, respectively, the moving average models of 8.4% - table 16a). The profitability of contrarian trading rules differs significantly from that of trend-following rules. The trading rules SG 1 to SG 3 produce an average gross rate of return of 6.4%, whereas the rules SG 4 to SG 6 realize an annual gross return of 10.9%. 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 significantly 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.

The (relative) performance of the 2580 trading systems by type of model and trading rule is different in two respects when trading in the DAX futures market as compared to the S&P 500 market (table 16b). First, moving average models and momentum models perform best producing a gross rate of return of 23.7% and 28.0%, respectively, whereas RSIN models make a gross return of only 13.6% per year. Second, trend-following and contrarian rules perform equally well, the rules SG 1 to SG 3 produce a gross rate of return of 23.4% on average, the rules SG 4 to SG 6 of 23.0%.

In the S&P 500 market as well as in the DAX market almost all of the 2580 technical models are profitable (98.7% and 97.6%, respectively, produce a positive gross rate of return).

Tables 17a and 17b classify all models according to the t-statistic of the means of the single returns into 5 groups. In the S&P 500 market 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 (1983/2000). 32.6% of the models achieve a t-statistic between 2.0 and 3.0. Hence, 60.9% of the trading systems produce an 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.

The results obtained when testing the models in the DAX market are similar (table 17b). 49.3% of all models achieve a t-statistic greater than 2.0, in 20.5% of the cases the t-statistic even exceeds 3.0 (these models produce an gross rate of return of 40.7% per year between 1997 and 2000 - the net rate of return is by 7.6 percentage points smaller since most of these models are "fast", e. g., they generate more trading signals than on average over all models).

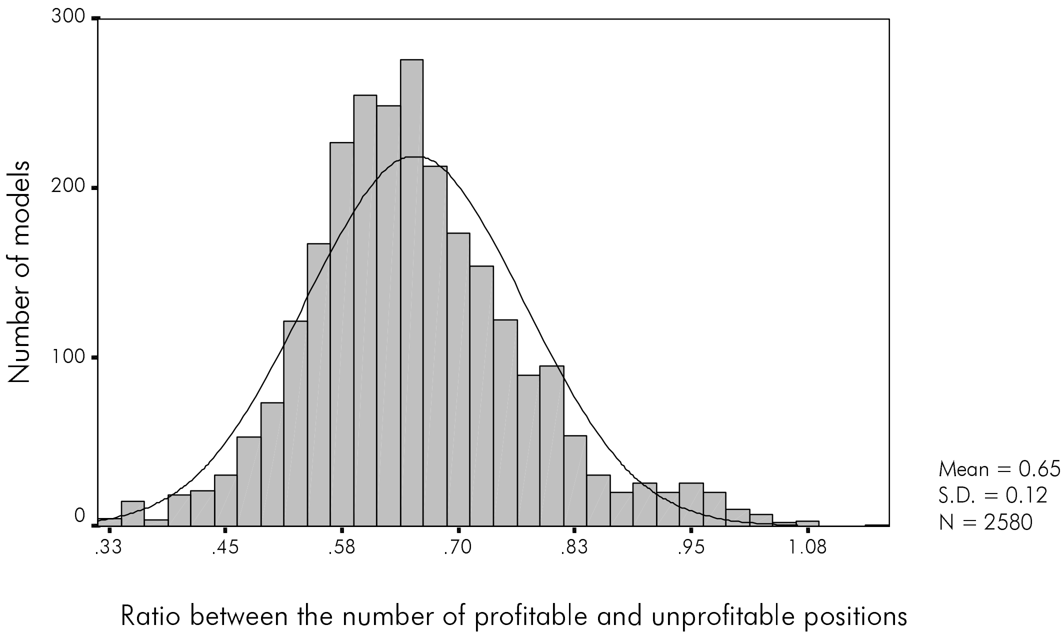
Table 17a: Components of 2580 trading systems by classes of the t-statistic and subperiods

S & P 500 futures market, 30-minutes-data, 1983-2000

t-statistic of the mean of the single returns	Number of models	Share of profitable models	Gross rate of return	Net rate of return	t-statistic	Mean for each class of models					
						Profitable positions			Unprofitable positions		
						Number	Return per day	Duration in days	Number	Return per day	Duration in days
1983-1985											
<0	837	32.4	–5.6	–8.2	–0.87	50.4	0.26	3.5	78.5	–0.41	1.6
0-<1	692	26.8	3.2	–0.5	0.49	73.1	0.30	2.8	113.2	–0.46	1.1
1-<2	561	21.7	9.8	4.4	1.46	100.2	0.35	2.2	166.5	–0.54	0.8
2-<3.0	277	10.7	16.7	10.0	2.47	139.0	0.47	1.5	196.0	–0.62	0.7
>3	213	8.3	25.8	18.3	3.64	164.1	0.54	1.1	208.7	–0.64	0.6
Total	2,580	100.0	5.1	0.7	0.73	86.2	0.34	2.6	130.3	–0.49	1.1
1986-1988											
<0	207	8.0	–3.7	–8.1	–0.26	75.5	0.45	3.4	145.0	–0.79	1.1
0-<1	1,267	49.1	7.7	2.8	0.58	88.2	0.52	2.7	153.2	–0.80	0.9
1-<2	945	36.6	18.2	13.5	1.39	94.8	0.54	2.3	141.8	–0.76	1.0
2-<3.0	154	6.0	30.1	24.9	2.29	115.5	0.62	1.8	144.6	–0.75	1.0
>3	7	0.3	44.9	38.5	3.14	143.2	0.62	1.8	169.9	–0.71	1.0
Total	2,580	100.0	12.1	7.3	0.92	91.4	0.53	2.5	147.9	–0.78	1.0
1989-1991											
<0	46	1.8	–1.8	–3.9	–0.22	35.4	0.26	5.4	66.5	–0.37	2.1
0-<1	396	15.3	4.5	1.8	0.57	48.4	0.30	4.0	84.0	–0.43	1.5
1-<2	890	34.5	12.0	8.3	1.52	70.1	0.36	2.9	109.7	–0.52	1.1
2-<3.0	923	35.8	19.8	14.6	2.47	106.0	0.43	2.1	152.4	–0.61	0.8
>3	325	12.6	27.7	19.7	3.43	160.6	0.52	1.4	240.2	–0.73	0.5
Total	2,580	100.0	15.4	10.8	1.93	90.4	0.40	2.6	136.7	–0.56	1.0
1992-1994											
<0	1,021	39.6	–4.0	–7.0	–0.89	52.4	0.20	3.2	99.5	–0.32	1.3
0-<1	727	28.2	2.3	–1.9	0.50	78.4	0.26	2.3	128.4	–0.41	1.0
1-<2	520	20.2	7.0	2.2	1.46	96.3	0.31	2.3	143.4	–0.40	1.3
2-<3.0	255	9.9	12.2	5.5	2.44	139.1	0.36	1.7	191.2	–0.43	1.0
>3	57	2.2	18.5	10.6	3.41	168.0	0.37	1.4	219.4	–0.41	0.8
Total	2,580	100.0	2.1	–2.1	0.40	79.7	0.26	2.6	128.2	–0.37	1.2
1995-1997											
<0	258	10.0	–2.0	–5.3	–0.29	64.8	0.30	2.9	100.3	–0.46	1.4
0-<1	1,273	49.3	3.5	0.0	0.55	66.9	0.30	3.0	103.5	–0.50	1.2
1-<2	737	28.6	9.2	4.1	1.40	97.7	0.38	2.2	152.9	–0.60	0.8
2-<3.0	253	9.8	17.2	9.0	2.42	156.9	0.46	1.4	250.7	–0.67	0.5
>3	59	2.3	24.3	14.2	3.35	196.8	0.49	1.0	300.1	–0.72	0.3
Total	2,580	100.0	6.4	1.9	0.95	87.3	0.34	2.6	136.2	–0.55	1.0
1998-2000											
<0	123	4.8	–3.3	–9.6	–0.30	120.3	0.58	2.0	188.0	–0.78	1.0
0-<1	681	26.4	6.3	0.8	0.61	105.3	0.54	2.3	166.7	–0.79	0.9
1-<2	1,610	62.4	14.7	10.2	1.46	84.4	0.48	3.0	140.8	–0.75	1.0
2-<3.0	165	6.4	22.6	17.6	2.21	92.5	0.52	2.8	153.8	–0.75	0.9
>3	1	0.0	26.5	22.3	3.04	90.7	0.79	1.2	118.1	–0.97	0.5
Total	2,580	100.0	12.1	7.2	1.20	92.2	0.50	2.7	150.7	–0.76	0.9
1983-2000											
<0	33	1.3	–0.9	–3.0	–0.25	38.2	0.24	5.4	64.8	–0.37	2.1
0-<1	216	8.4	2.3	–0.3	0.67	47.2	0.29	4.2	77.8	–0.43	1.6
1-<2	760	29.5	5.2	2.1	1.53	58.7	0.34	3.2	93.5	–0.50	1.3
2-<3.0	840	32.6	8.9	4.5	2.51	82.7	0.39	2.4	132.1	–0.59	0.9
>3	731	28.3	14.9	7.9	3.93	137.5	0.51	1.5	211.8	–0.73	0.6
Total	2,580	100.0	8.8	4.3	2.43	87.6	0.40	2.6	137.9	–0.59	1.0

Table 17a (17b) also shows how the technical models perform in the S&P 500 (DAX) futures market over 6 subperiods since 1983 (4 subperiods since 1997). 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. In the S&P 500 market the 2580 models perform best over the subperiods 1989/91, 1986/88 and 1998/2000, and they perform worst between 1983 and 1985 and between 1992 and 1994. In the DAX market the models perform poorly over the year 1999, over the 3 other subperiods the models produce high returns.

Figure 17a: 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

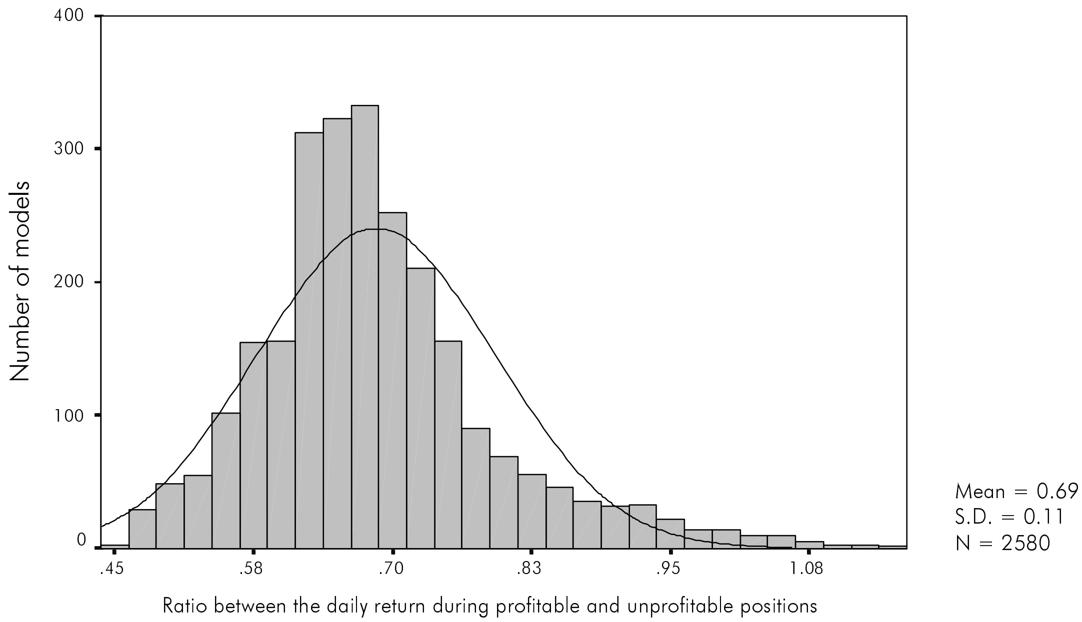


6.3 The pattern of profitability of the trading systems

A comparison between figures 17a, 18a, and 19a on the one hand, and figures 17b, 18b and 19b on the other hand reveals that the pattern of profitability of technical stock trading based on 30-minutes-data in the S&P 500 market and in the DAX market is very similar. Profitable positions occur on average by 35% less frequently in trading S&P 500 futures as compared to 34% in trading DAX futures (figures 17a/b). The daily return during profitable positions is by 31% lower than during unprofitable positions in both markets (figures 18a/b). Hence, the high ratio between the average duration of profitable and unprofitable positions – it reflects the systematic exploitation of persistent price movements by technical models – is the main reason for the profitability of technical stock trading also when 30-minutes-data are used. This ratio amounts to 2.74 in the S&P 500 market, and to 2.86 in the DAX market (figures 19a/b).

Not only are the means of the three ratios of profitability components almost identical in the S&P 500 and in the DAX market, but also the shape of their distributions is very similar in both markets.

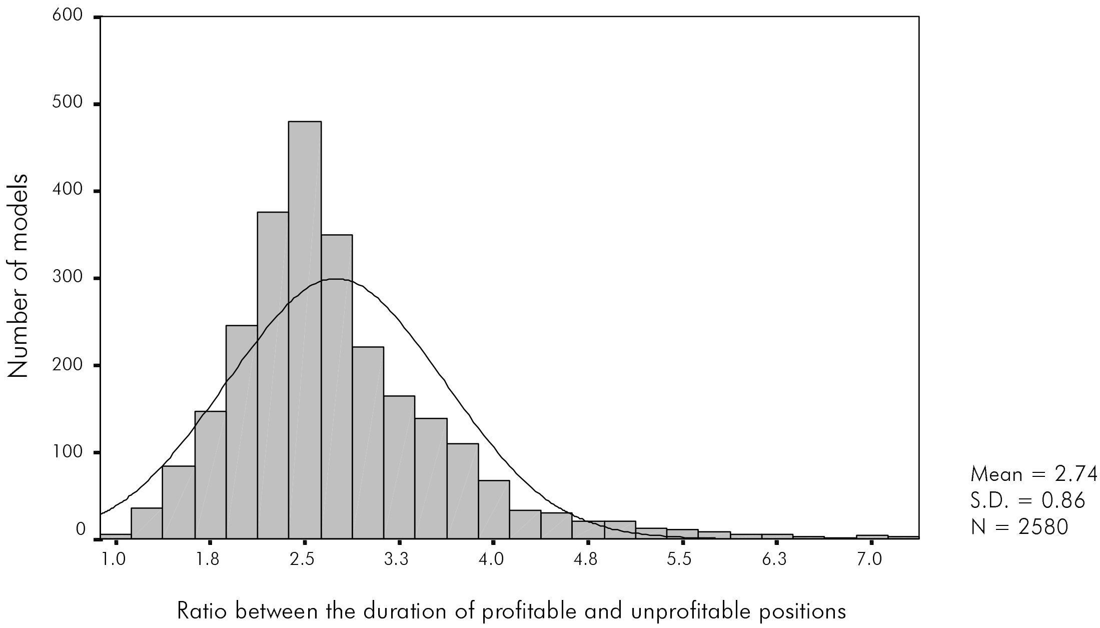
Figure 18a: Distribution of 2580 trading systems by the ratio between the daily return during profitable and unprofitable positions 1983-2000
S&P 500 futures market, 30 minutes data



Tables 18a and 18b show the distribution of the three ratios of profitability components (complemented by the ratio between the return per profitable and unprofitable position) among three classes of these ratios (additionally differentiated by their t-statistic). The tables summarize the pattern of profitability which is most typical for technical trading systems. 83.5% of all models (S&P 500 trading) produce a number of profitable trades which is by more than 20% smaller than the number of unprofitable positions. In only 3.1% of all cases does the number of profitable positions exceed the number of unprofitable positions. The average return per day during profitable positions is in most cases (60.8%) by more than 30% lower than the daily return (in absolute terms) during unprofitable positions. For 46.1% of all models the average duration of profitable positions is between 2.5 and 4.0 times longer than the duration of unprofitable positions.

Figure 19a: 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



This pattern of profitability is characteristic for all types of models. There are, however, some quantitative differences. Momentum models produce comparatively high ratios between the average duration of profitable and unprofitable positions (relative to the two other types of models), in the case of moving average models the ratios between the number of profitable and unprofitable positions is comparatively high, and RSIN models produce comparatively high ratios between the average return during profitable and unprofitable positions.

When trading DAX futures based on 30-minute-data he models exhibit the same pattern of profitability as in the S&P 500 market (table 18b).

Table 18a: Distribution of technical trading systems by the ratio of the profit components S & P 500 futures market, 30-minutes-data, 1983-2000

	NPP/NPL			RPP/RPL			DRP/DRL			DPP/DPL		
t-statistic of the mean of the single returns	<0.8	0.8-1.0	>1	<2	2.0-3.0	>3	<0.7	0.7-0.8	>0.8	<2.5	2.5-4	>4
Moving average models												
<0	94.7	4.9	0.4	96.4	3.0	0.5	75.3	17.3	7.4	67.6	30.2	2.2
0-<1	87.9	10.5	1.6	88.0	11.7	0.3	69.2	21.1	9.7	46.3	48.5	5.2
1-<2	82.0	14.8	3.2	75.8	23.4	0.8	63.3	23.0	13.7	40.5	51.4	8.1
2-<3.0	62.8	28.0	9.2	75.7	22.6	1.7	46.8	22.2	31.0	54.5	37.0	8.5
>3	56.7	33.6	9.7	70.9	27.5	1.5	33.5	21.9	44.6	62.5	26.5	11.0
Total	80.5	15.7	3.8	81.3	17.9	0.8	61.8	21.6	16.6	49.0	44.1	6.8
Momentum models												
<0	100.0	–	–	92.5	7.5	–	94.3	5.7	-	6.2	88.4	5.4
0-<1	98.6	1.4	–	79.1	20.9	–	91.5	7.6	0.9	10.0	75.6	14.4
1-<2	98.5	1.5	–	68.4	31.6	–	83.0	14.2	2.8	15.2	72.6	12.2
2-<3.0	96.8	3.2	–	67.2	32.8	–	66.9	23.4	9.7	24.9	70.1	5.0
>3	96.6	3.4	–	85.5	14.5	–	69.4	29.3	1.4	26.4	72.8	0.8
Total	98.1	1.9	–	74.5	25.5	–	81.6	15.0	3.4	16.1	74.2	9.7
Relative strength models												
<0	100.0	–	–	94.6	5.4	–	22.7	39.9	37.4	71.9	28.1	–
0-<1	100.0	–	–	82.5	17.5	–	32.5	32.3	35.2	66.7	33.2	0.2
1-<2	100.0	–	–	73.1	26.9	–	30.2	33.7	36.1	56.4	43.6	–
2-<3.0	99.6	0.4	–	83.7	16.3	–	29.9	41.4	28.7	59.3	40.7	–
>3	90.8	9.2	–	92.7	7.3	–	29.9	44.9	25.2	61.2	38.8	–
Total	98.6	1.4	–	81.7	18.3	–	30.3	36.8	32.9	61.2	38.7	0.0
All models												
<0	95.3	4.4	0.4	96.1	3.4	0.5	74.4	17.4	8.1	64.0	33.7	2.3
0-<1	89.8	8.9	1.3	86.8	12.9	0.2	67.8	21.0	11.2	45.2	49.3	5.5
1-<2	84.7	12.6	2.7	75.0	24.3	0.7	62.3	23.1	14.6	39.7	52.4	7.8
2-<3.0	70.1	22.6	7.3	75.6	23.0	1.4	47.2	24.2	28.5	51.9	40.9	7.3
>3	66.4	26.5	7.1	76.1	22.8	1.1	36.3	26.5	37.2	58.8	33.0	8.2
Total	83.5	13.4	3.1	80.8	18.5	0.7	60.8	22.3	16.9	47.4	46.1	6.5

NPP (NPL) . . . Number of profitable (unprofitable) positions per year.
RPP (RPL) . . . Average return per profitable (unprofitable) position.
DRP (DRL) . . . Retern per day during profitable (unprofitable) positions.
DPP (DPL) . . . Average duration of profitable (unprofitable) positions.

The rations are calculated in absolute terms, i.e., the negative sign of returns of unprofitable positions is neglected.

Table 19a: Cluster of 2,580 trading systems according to profit components
S & P 500 futures market, 30-minutes-data, 1983-2000

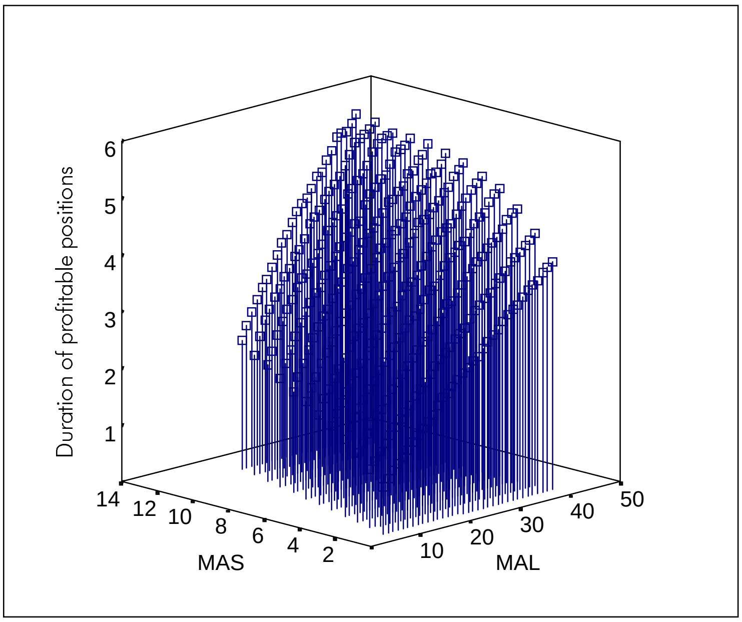
	Number of models	Mean of gross rate of return	Mean for each class of models					
			Profitable positions			Unprofitable positions		
			Number	Return per day	Duration in days	Number	Return per day	Duration in days
Moving average models								
Cluster 1	52	18.9	207.6	0.62	1.0	360.0	– 0.85	0.3
Cluster 2	399	13.6	118.8	0.46	1.8	204.8	– 0.71	0.5
Cluster 3	1,673	6.9	60.0	0.36	3.1	89.7	– 0.52	1.3
Total	2,124	8.4	74.7	0.39	2.8	118.0	– 0.57	1.1
Momentum models								
Cluster 1	48	15.3	258.2	0.63	0.8	379.6	– 0.90	0.3
Cluster 2	137	9.6	134.0	0.39	1.7	221.4	– 0.68	0.5
Cluster 3	43	5.7	66.7	0.29	3.3	121.8	– 0.49	1.0
Total	228	10.1	147.5	0.42	1.8	235.9	– 0.69	0.5
Relative strength models								
Cluster 1	51	16.9	303.2	0.68	0.7	439.6	– 0.95	0.3
Cluster 2	95	12.1	135.8	0.50	1.3	206.0	– 0.68	0.5
Cluster 3	82	7.5	66.3	0.38	2.7	115.4	– 0.46	1.2
Total	228	11.5	148.3	0.50	1.7	225.7	– 0.66	0.7
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

6.4 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 divide all models into similar groups in the following way. All cases (models) characterized by the realization of a certain number of variables (components of the profitability of technical models in our case) are assigned to different clusters under the condition that the differences between the models (with respect to the selected variables) are minimized within each cluster and maximized across the clusters. Since this exercise was carried out only for a descriptive classification of technical models 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 19a and 19b 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). Cluster 1 comprises therefore 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.

Figure 20a: Duration of profitable positions and the parameters of trading systems (moving average models (SG1))
S&P 500 futures market, 30 minutes data



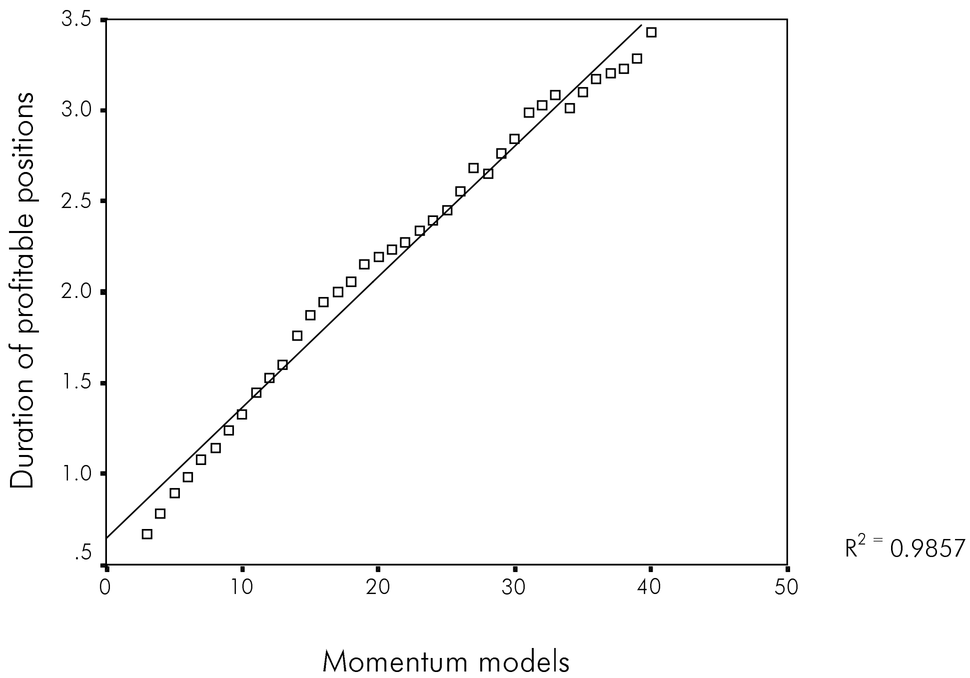
The average gross rates of return differ significantly across the three clusters. The "fast" models of cluster 1 perform by far best. These models produce an average gross rate of return of 17.1% in the S&P 500 market, and of 27.6% in the DAX market, respectively. Also the models of cluster 2 achieve an gross rate of return which is higher than on average over all 2580 models. However, the models of cluster 3 – being relatively slow – produce an average gross rate of return of only 6.9% when trading S&P 500 futures. In the DAX market the models of cluster 3 perform much better (GRR: 21.1%) though slightly worse than on average over all models.

6.5 Parameters of technical models and their trading behavior

A clear relationship prevails between the size of the parameters of technical models and their "speed" and, hence, the average duration of the profitable positions they generate. In the case of moving average models (figures 20a and 20b), the number of open positions and, hence, the duration of the profitable positions increase with the difference between the length of the short-term and the long-term moving averages (the smaller this difference is the more crossovers occur between both moving averages).

Figures 21a and 21b show that the average duration of profitable positions produced by momentum models increases almost monotonically with the size of the time span i.

Figure 21a: Duration of profitable positions and the parameters of trading systems (momentum models (SG1))
S&P 500 futures market, 30 minutes data



7. The performance of technical trading systems based on 30-minutes-futures-prices over subperiods in and out of sample

The study subdivides the overall sample period of 18 years (S&P 500 futures trading) into 6 subperiods each lasting 3 years. Since the sample period for testing technical trading models in the DAX futures market lasts only from 1997 to 2000 the 4 calendar years are taken as subperiods.

First, I explore how all 2580 trading models perform over the subperiods. For each subperiod I then examine the performance of the most profitable models over the next following subperiod (comparison of their performance in sample and out of sample).

7.1 Performance of all models by subperiods

Table 20a shows that 40.0% of all models produce a positive gross rate of return over each subperiod when trading S&P 500 future contracts. The share of stable models is highest among RSIN systems (51.8%) and momentum systems (48.2%). When trading DAX futures 37.9% of all models are profitable in each subperiod (table 20b).

In the S&P 500 market the share of stable models (51.6%) is much higher among contrarian models (SG 4 to SG 6) than among trend-following models (26.1%). This relationships holds also true in the case of DAX trading, it is, however, less pronounced.

Stable models produce significantly higher returns as compared to unstable models. When trading S&P 500 futures the 1031 stable models produce a gross (net) rate of return of 12.7% (6.6%) on average, the unstable models, achieve only a gross (net) rate of return of 6.2% (2.7%). In the DAX market the 977 stable models produce a gross (net) rate of return of 29.1% (21.7%), the unstable models of only 19.6% (14.4%).

The stable and more profitable models are at the same time relatively "fast" models, hence, the difference between gross and net returns is in general larger in the case of stable models as compared to unstable models.

Table 20a: Frequency and performance of stable and unstable trading models
S & P 500 futures market, 30-minutes-data, 1983-2000

	Number of models		Share of stable models	Stable models[21])			Unstable models[1])		
	Stable	Unstable		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 models									
SG 1	58	296	16.4	14.2	6.5	3.41	5.7	1.9	1.50
SG 2	28	326	7.9	10.1	6.4	2.84	3.9	1.7	1.17
SG 3	181	173	51.1	9.1	5.4	2.95	5.1	2.7	1.74
SG 4	171	183	48.3	14.6	8.9	3.66	9.2	5.8	2.44
SG 5	180	174	50.8	12.6	6.9	3.54	6.2	3.0	1.89
SG 6	185	169	52.3	13.6	7.9	3.57	7.2	3.8	2.03
Total	803	1321	37.8	12.5	7.2	3.40	5.9	2.9	1.70
Momentum models									
SG 1	13	25	34.2	13.1	4.8	3.16	7.7	0.7	1.95
SG 2	9	29	23.7	10.4	5.1	2.67	5.8	1.8	1.53
SG 3	18	20	47.4	11.4	4.2	3.13	6.4	0.4	1.78
SG 4	25	13	65.8	14.3	4.2	3.53	9.0	– 0.6	2.28
SG 5	22	16	57.9	13.1	3.7	3.41	8.1	0.3	2.22
SG 6	23	15	60.5	13.6	3.8	3.46	9.1	0.2	2.38
Total	110	118	48.2	13.0	4.1	3.31	7.4	0.7	1.95
Relative strength models									
SG 4	26	50	34.2	17.1	7.2	4.10	9.7	3.6	2.35
SG 5	54	22	71.1	12.2	4.4	3.65	7.4	0.7	2.27
SG 6	38	38	50.0	14.9	5.3	3.89	8.2	2.3	2.19
Total	118	110	51.8	14.2	5.3	3.83	8.7	2.6	2.28
All models									
SG 1	71	321	18.1	14.0	6.2	3.36	5.8	1.8	1.53
SG 2	37	355	9.4	10.2	6.1	2.80	4.1	1.7	1.20
SG 3	199	193	50.8	9.3	5.3	2.96	5.3	2.5	1.75
SG 4	222	246	47.4	14.9	8.2	3.70	9.3	5.0	2.41
SG 5	256	212	54.7	12.5	6.1	3.55	6.5	2.6	1.96
SG 6	246	222	52.6	13.8	7.1	3.61	7.5	3.3	2.08
Total	1031	1549	40.0	12.7	6.6	3.44	6.2	2.7	1.76

The relationship between the average duration of profitable positions of technical models and their profitability over subperiods is shown more in detail in tables 21a and 21b. In the S&P 500 market as well as in the DAX market the share of stable models is the smaller the longer their profitable positions last on average. In the case of S&P 500 trading, e. g., this share amounts to 81.5% for short-term models, to 69.7% for medium-term models

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

and to only 26.0% for long-term models. At the same time also the overall gross rate of return is on average the lower the longer the profitable positions of technical models last on average. These relationships provide indirect evidence in favor of the hypothesis that the increased "speed" of trading – fostered by the new information and communication and information technologies – has caused persistent stock price runs to occur in the 1980s and 1990s primarily over very short-term periods. This phenomenon seems to have affected the profitability of technical stock trading in two ways. First, persistent price runs can be identified and exploited only on the basis of intraday price data. Second, even on the basis of, e. g., 30-minutes-data those ("fast") models perform best for which the average duration of profitable positions lasts on average less than one day.

Tables 22a and 22b show the average performance of the 3 types of technical models over each subperiod. In S&P 500 futures trading more than 90% of the RSIN models produce a positive gross rate of return over each subperiod (except for the period 1998/2000 when only 81.6% of all RSIN models are profitable). The profitability of momentum models is similarly stable (they perform significantly worse only over the period 1992/94). The profitability of moving average models is comparatively less stable since only 61.6% and 56.2% of these models produce a positive gross rate of return between 1983 and 1985, and between 1992 and 1994, respectively.

When trading DAX futures the share of profitable models is close to or higher than 80% over all subperiods except for the year 1999 (table 22b).

Tables 23a and 23b show the average performance of the 6 types of trading rules over each subperiod. As has already be demonstrated in tables 20a/b the contrarian systems (SG 4 to SG 6) achieve the most stable profitability. In most cases more than 80% of these models produce a positive gross rate of return except for the year 1999 when trading DAX futures.

Table 21a: Frequency and performance of stable and unstable trading systems
S & P 500 futures market, 30-minutes-data, 1983-2000

t-statistic of the mean of the single returns	Number of models		Share of stable models	Stable models[22])		Unstable models[1])	
	Stable	Unstable		Gross rate of return	Net rate of return	Gross rate of return	Net rate of return
Short-term models (cluster 1)							
<0	–	–	–	–	–	–	–
0-<1	–	1	0.0	–	–	2.5	– 8.7
1-<2	–	2	0.0	–	–	5.1	– 8.5
2-<3.0	4	8	33.3	11.2	– 1.7	9.9	– 4.2
>3	119	17	87.5	18.4	5.6	15.5	0.8
Total	123	28	81.5	18.1	5.4	12.7	– 1.6
Medium-term models (cluster 2)							
<0	–	–		–	–	–	–
0-<1	–	4	0.0	–	–	2.9	– 3.0
1-<2	10	54	15.6	6.0	– 0.5	6.1	– 0.1
2-<3.0	103	107	49.0	10.0	3.8	9.7	3.0
>3	327	26	92.6	15.4	8.4	14.4	7.6
Total	440	191	69.7	13.9	7.1	9.2	2.6
Long-term models (cluster 3)							
<0	–	33	0.0	–	–	– 0.9	– 3.0
0-<1	–	211	0.0	–	–	2.3	– 0.2
1-<2	29	665	4.2	6.0	2.8	5.1	2.4
2-<3.0	241	377	39.0	8.8	5.1	8.3	5.0
>3	198	44	81.8	12.5	8.7	12.7	8.9
Total	468	1,330	26.0	10.2	6.5	5.7	2.8
All models							
<0	–	33	–	–	–	– 0.9	– 3.0
0-<1	–	216	0.0	–	–	2.3	– 0.3
1-<2	39	721	5.1	6.0	2.0	5.2	2.1
2-<3.0	348	492	41.4	9.2	4.6	8.7	4.4
>3	644	87	88.1	15.1	8.0	13.8	6.9
Total	1,031	1,549	40.0	12.7	6.6	6.2	2.7

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

Table 22a: Performance of 2580 technical trading systems by types of models and subperiods
S & P 500 futures market, 30-minutes-data, 1983-2000

	Number of models		Share of profitable models in %	Gross rate of return	t-statistic	Net rate of return	Duration of profitable positions
	Profitable	Total					
1983-1985							
Moving average models	1,308	2,124	61.6	3.8	0.55	– 0.0	2.8
Momentum models	217	228	95.2	11.4	1.60	4.1	1.9
Relative strength models	215	228	94.3	11.4	1.60	4.4	1.8
Total	1,740	2,580	67.4	5.1	0.73	0.7	2.6
1986-1988							
Moving average models	1,967	2,124	92.6	12.0	0.93	7.8	2.7
Momentum models	181	228	79.4	8.3	0.56	0.1	1.7
Relative strength models	223	228	97.8	16.5	1.13	8.9	1.7
Total	2,371	2,580	91.9	12.1	0.92	7.3	2.5
1989-1991							
Moving average models	2,083	2,124	98.1	15.1	1.90	11.2	2.8
Momentum models	228	228	100.0	17.0	2.04	9.3	1.8
Relative strength models	223	228	97.8	16.1	2.04	8.4	1.5
Total	2,534	2,580	98.2	15.4	1.93	10.8	2.6
1992-1994							
Moving average models	1,194	2,124	56.2	1.5	0.27	– 2.0	2.7
Momentum models	145	228	63.6	2.3	0.47	– 5.3	1.6
Relative strength models	219	228	96.1	7.8	1.53	0.2	1.8
Total	1,558	2,580	60.4	2.1	0.40	– 2.1	2.6
1995-1997							
Moving average models	1,907	2,124	89.8	5.8	0.88	2.0	2.7
Momentum models	199	228	87.3	7.7	1.09	– 0.1	1.8
Relative strength models	216	228	94.7	10.6	1.49	2.9	1.6
Total	2,322	2,580	90.0	6.4	0.95	1.9	2.6
1998-2000							
Moving average models	2,046	2,124	96.3	12.5	1.24	8.2	3.0
Momentum models	224	228	98.2	14.0	1.34	6.1	1.9
Relative strength models	186	228	81.6	7.1	0.75	– 0.7	1.6
Total	2,456	2,580	95.2	12.1	1.20	7.2	2.7

Table 23a: Performance of 2,580 technical trading systems by types of models and subperiods
S & P 500 futures market, 30-minutes-data, 1983-2000

	Number of models		Share of profitable models	Gross rate of return	t-statistic	Net rate of return	Duration of profitable positions
	Profitable	Total					
1983-1985							
SG 1	263	392	67.1	3.9	0.53	– 0.6	3.4
SG 2	148	392	37.8	– 0.4	– 0.11	– 2.8	3.7
SG 3	283	392	72.2	3.8	0.72	0.5	2.0
SG 4	357	468	76.3	8.2	1.06	3.0	2.6
SG 5	346	468	73.9	6.6	1.02	1.6	1.9
SG 6	343	468	73.3	7.2	0.99	1.9	2.2
Total	1,740	2,580	67.4	5.1	0.73	0.7	2.6
1983-1985							
SG 1	322	392	82.1	6.4	0.47	1.5	3.3
SG 2	302	392	77.0	4.5	0.37	1.6	3.5
SG 3	370	392	94.4	10.0	0.86	6.2	2.1
SG 4	460	468	98.3	19.5	1.38	13.8	2.5
SG 5	457	468	97.6	13.1	1.02	7.6	2.0
SG 6	460	468	98.3	16.6	1.23	10.8	2.2
Total	2,371	2,580	91.9	12.1	0.92	7.3	2.5
1989-1991							
SG 1	375	392	95.7	12.7	1.43	8.1	3.5
SG 2	368	392	93.9	7.7	1.02	5.2	3.9
SG 3	392	392	100.0	12.0	1.85	8.5	2.1
SG 4	464	468	99.1	20.9	2.36	15.4	2.5
SG 5	468	468	100.0	17.1	2.26	11.7	2.0
SG 6	467	468	99.8	19.7	2.39	14.1	2.2
Total	2,534	2,580	98.2	15.4	1.93	10.8	2.6
1992-1994							
SG 1	84	392	21.4	– 4.0	– 0.77	– 9.2	3.2
SG 2	48	392	12.2	– 3.4	– 0.87	– 5.4	3.5
SG 3	237	392	60.5	0.9	0.32	– 1.9	1.6
SG 4	456	468	97.4	8.8	1.60	4.1	3.1
SG 5	315	468	67.3	2.7	0.62	– 2.5	1.7
SG 6	418	468	89.3	5.6	1.10	0.6	2.4
Total	1,558	2,580	60.4	2.1	0.40	– 2.1	2.6
1995-1997							
SG 1	367	392	93.6	8.0	1.07	3.2	3.4
SG 2	342	392	87.2	3.9	0.65	1.6	3.7
SG 3	381	392	97.2	5.0	0.95	1.7	1.9
SG 4	396	468	84.6	7.0	0.91	1.5	2.5
SG 5	441	468	94.2	7.4	1.17	2.1	1.9
SG 6	395	468	84.4	6.8	0.96	1.3	2.2
Total	2,322	2,580	90.0	6.4	0.95	1.9	2.6
1998-2000							
SG 1	391	392	99.7	17.0	1.55	12.5	3.6
SG 2	392	392	100.0	15.7	1.60	12.8	3.9
SG 3	392	392	100.0	12.5	1.39	8.5	2.4
SG 4	387	468	82.7	7.7	0.69	1.6	2.5
SG 5	462	468	98.7	12.2	1.25	6.6	2.1
SG 6	432	468	92.3	9.2	0.88	3.2	2.2
Total	2,456	2,580	95.2	12.1	1.20	7.2	2.7

7.2 Performance of the 25 best models in sample and out of sample

The fact that almost all of 2580 trading models produce excess returns over the entire sample period in the S&P 500 market as well as in the DAX market, the fact that roughly 40% of the models are profitable in each subperiod, as well as the specific pattern of the models' profitability (which is typical for the performance of practically all technical trading systems), make it rather implausible that the ex-post performance of technical stock futures trading based on 30-minute-data is (mainly) the result of data snooping. To put it differently: if the S&P 500 as well as the DAX futures prices had actually followed a random walk, then a test of 2580 technical models over such long sample periods could not have produced these results (the sample period covers 62727 observations in the case of S&P 500 trading, and 17688 observations in the case of DAX trading, respectively).

However, the fact that persistent stock price runs of varying lengths occur more frequently than can be expected in the case of a random walk (causing profitable positions signaled by technical models to last several times longer than unprofitable positions) does not ensure the profitability of technical trading ex ante, at least not in excess of the "normal" returns one could expect from a random selection of technical models. If, for example, a trader selects a model that would have performed best over the most recent past for trading over a subsequent period, then he might become a victim of his own "model mining" for the following reason.

The ex-post profitability of the best models consist of two components. The first stems from the "normal" non-randomness of stock price dynamics, namely, the occurrence of persistent price 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 (the importance of this second component increases as more models are tested and the test period is shortened). Now, if the "optimal" profitability of a selected model is mainly the result of this "model mining" then this model will perform much worse over the subsequent period. However, if the in-sample profitability stems mainly from the exploitation of persistent stock price trends then it might be reproduced out of sample (provided that the lengths of the trends do not change strongly over time).

In order to investigate this matter, the following exercise was 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.

Table 24a: Performance of the 25 most profitable trading systems by subperiods
In sample and out of sample
S & P 500 futures market, 30-minutes-data, 1983-2000

	Number	Gross rate of return	t-statistic	Net rate of return	Duration of profitable positions	Number	Gross rate of return	t-statistic	Net rate of return	Duration of profitable positions
			In sample					Out of sample		
1983-1985										
Short	2	38.5	4.82	28.57	1.1					
Medium	22	34.9	4.49	28.61	1.5					
Long	1	33.8	4.24	29.00	1.7					
Total	25	35.2	4.51	28.62	1.4					
1986-1988										
Short	4	43.7	2.64	32.92	1.1	2	41.6	2.42	30.7	1.0
Medium	6	46.9	2.96	37.89	1.1	22	27.6	1.65	20.4	1.4
Long	15	38.8	2.77	34.67	2.2	1	29.4	1.80	23.6	1.7
Total	25	41.6	2.80	35.16	1.7	25	28.8	1.72	21.3	1.4
1989-1991										
Short	8	38.1	4.42	27.32	1.0	4	29.8	3.33	19.0	1.0
Medium	16	34.9	4.04	28.04	1.5	6	31.6	3.64	22.2	1.0
Long	1	29.3	3.41	25.46	2.4	15	24.6	2.90	20.5	2.2
Total	25	35.7	4.14	27.71	1.4	25	27.1	3.15	20.7	1.7
1992-1994										
Short	4	21.7	3.78	13.96	1.3	8	18.6	3.37	9.6	1.2
Medium	8	18.8	3.42	13.77	1.8	16	13.9	2.61	8.3	1.6
Long	13	17.0	3.09	14.19	3.2	1	6.5	1.17	3.9	3.3
Total	25	18.3	3.31	14.02	2.4	25	15.1	2.79	8.5	1.5
1995-1997										
Short	9	27.6	3.60	17.15	1.2	4	9.8	1.24	−0.9	1.0
Medium	14	25.1	3.31	17.48	1.6	8	10.5	1.35	3.7	1.4
Long	2	19.6	2.30	16.43	3.4	13	5.5	0.70	1.4	2.2
Total	25	25.6	3.33	17.27	1.6	25	7.8	1.00	1.7	1.7
1998-2000										
Short	-	-	-	-	-	9	15.0	1.33	3.9	1.2
Medium	10	27.3	2.40	21.76	2.5	14	15.9	1.44	8.0	1.6
Long	15	25.1	2.38	21.86	3.9	2	3.1	0.27	−0.2	3.4
Total	25	26.0	2.39	21.82	3.3	25	14.6	1.30	5.9	1.6

Table 24a gives the main results for trading S&P 500 futures which can be summarized as follows. First, the in-sample performance of the best models is much better than the average performance of all models. For example, the 25 best models produce an average gross rate of return over the six subperiods between 1983 and 2000 of 30.4%, whereas the average return of all models amounts to only 8.8% (tables 16a and 24a). This difference is in part due to the "model mining" bias as will be shown below. Second, most of the 25 best models "specialize" on exploiting medium-term and long-term 30-minutes-price-runs (they belong to cluster 2 and cluster 3). Out of 150 cases (25 best models and 6 subperiods) only 27 models are short-term models (cluster 1). Even though short-term models perform best on average over all models, the 25 single models which produce the highest net rate of return are in most cases medium-term and long-term models. Third, the out-of-sample profitability of the 25 best models selected on the basis of their performance over the most recent subperiod is significantly better than the average over all models. The best 25 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 25a). Fourth, the 25 best models produce on average positive ex-ante gross returns as well as net returns in each subperiod, in only 3 out of 125 cases do single models produce gross or net losses. Fifth, in some cases the difference between the performance of the best models in-sample and out-of-sample might also be due to changes in the average duration of profitable positions between two subsequent periods. Over the subperiod 1992/94, for example, the duration of profitable positions of the best models (in sample) amounted to 2.4 days, however, over the next subperiod faster models performed best. As a consequence, the (relatively slower) models used ex ante over this subperiod performed particularly worse compared to those models which (would have) produced the highest ex-post returns.

These five observations also hold true when comparing the in-sample and out-of-sample performance of the best models in the DAX futures market except for two facts. First, the difference between the profitability of the best models in-sample and out-of-sample is much greater as compared to trading S&P 500 futures (in the DAX market the 25 best models produce ex post a gross rate of return of 71.2% whereas the ex-ante-return amounts to only 22.3% - table 25b). Second, when trading DAX futures the 25 best models are on average unprofitable over one subperiod, e. g. the year 1999 (table 24b).

Tables 25a and 25b summarize 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 in sample and out of sample. In addition, t-statistics are calculated which test for the significance of the difference between the means of the best models and the means of all models.

Table 25a: 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

	Gross rate of return	Standard deviation	t-statistic
		All models (N = 12900)	
Gross rate of return	9.6	8.7	
Net rate of return	5.0	8.3	
NPP/NPL	0.65	0.14	
DRP/DRL	0.68	0.14	
DPP/DPL	2.80	0.92	
		The 25 most profitable models in sample (N = 125)	
Gross rate of return	29.4	8.8	24.9
Net rate of return	23.2	7.9	25.6
NPP/NPL	0.78	0.19	7.6
DRP/DRL	0.81	0.16	9.1
DPP/DPL	2.51	0.97	– 3.3
		The 25 most profitable models out of sample (N = 125)	
Gross rate of return	18.7	10.4	9.7
Net rate of return	11.6	10.1	7.3
NPP/NPL	0.78	0.16	9.1
DRP/DRL	0.81	0.13	11.1
DPP/DPL	2.13	0.82	– 9.1

When trading S&P 500 futures, 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 best models as compared to the average over all models). Consequently, the mean annual rate of return of the best models (29.4%) is roughly three times as high than the mean over all models (9.6%).

The profitability pattern of the best models out of sample is similar. The mean ratio between the number of profitable and unprofitable positions as well as the mean ratio between the daily return during profitable and unprofitable positions are also significantly higher in the case of the best models out of sample as compared to the average ratios over all models.

However, the ratio between the duration of profitable and unprofitable positions of the best models out of sample is lower than in sample and consequently significantly lower than in the case of all models. Hence, when trading S&P 500 futures that pattern which is typical for the 25 best models in sample can be reproduced out of sample. One can therefore conclude that there exists some non-randomness in the dynamics of 30-minutes-stock-prices which is sufficiently stable over time so that it can systematically be exploited by an optimizing technical stock futures trader.

A comparison of the pattern of profitability of the 25 best models in sample and out of sample in the DAX futures market shows a similar picture. However, the ratios of the three profitability components are lower out of sample than in sample in DAX trading as compared to S&P 500 trading. As a consequence, the difference in the profitability of the best models in sample and out of sample is greater in the DAX market as compared to the S&P 500 market (compare table 25b to 25a).

8. Aggregate positions and transactions of technical models based on 30-minutes-futures-prices and stock price dynamics

This section investigates the impact of the use of different trading models on stock price dynamics. In a first step an index of the aggregate transactions and open positions of the 2580 technical models is calculated for any point in time. Based on these indices, the concentration of transactions in terms of buys and sells and the concentration of position holding in terms of long and short is documented. The analysis shows that the great majority of the models produce signals indicating the same side of the market, either long or short. Finally, the relationship between the level and the change of the net position index and the stock ptice movements is analyzed.

8.1 The aggregation of trading signals

The open positions of the 2580 trading models are aggregated in the following way. The number +1 (-1) is assigned to any long (short) position of each single model (to any neutral position the number 0 is assigned). The net position index is then calculated for every 30-minutes-interval as the sum of these numbers over all models divided by the number of models (2580). Therefore, an index value of +100 (-100) means that 100% of the models hold a long (short) position. A value of 90 (-90) indicates that 95% of the models are long (short) and 5% short (long). The percentage share of models holding a long position can generally be derived from the value of the net position index (PI) as [PI+100]/2. So, if PI equals 0, then half the models signal a long position and half signal a short position.

The net transaction index (TI) is simply the first difference of the net position index. Its theoretical maximum (minimum) value is twice as high (in absolute terms) as in the case of the net position index since the number of transactions is always twice the number of open positions. The extreme value of +200 (-200) would be realized if all models change the open position from short to long (from long to short) between two consecutive trading intervals (implying 5160 buy transactions or sell transactions, respectively). This would imply a change in PI of +100 (-100) to –100 (+100).

The net position index shows the overhang of long positions over short positions (and vice versa) of all 2580 technical models at any point in time, whereas the net transaction index shows the excess demand for stock index futures stemming from these models. These indices are used to evaluate the impact of the trading behavior of technical models upon stock (futures) price movements.

In order to investigate the extent to which the signals from technical models balance each other, the components of the net transaction index are also documented, i.e., the number of buys and sells during each 30-minute-interval (divided by the number of all models). If, for example, 10% of all models switch from short to long positions during one trading interval and 10% of the models change their open positions in the opposite way then the value of the (gross) buy transaction index and the value of the (gross) sell transaction index compensate each other (the net position index and the net transaction index remain constant as long as signals of technical models balance each other).

Figure 22a: Aggregate trading signals and stock price dynamics
July and August 2000, 30-minutes-data

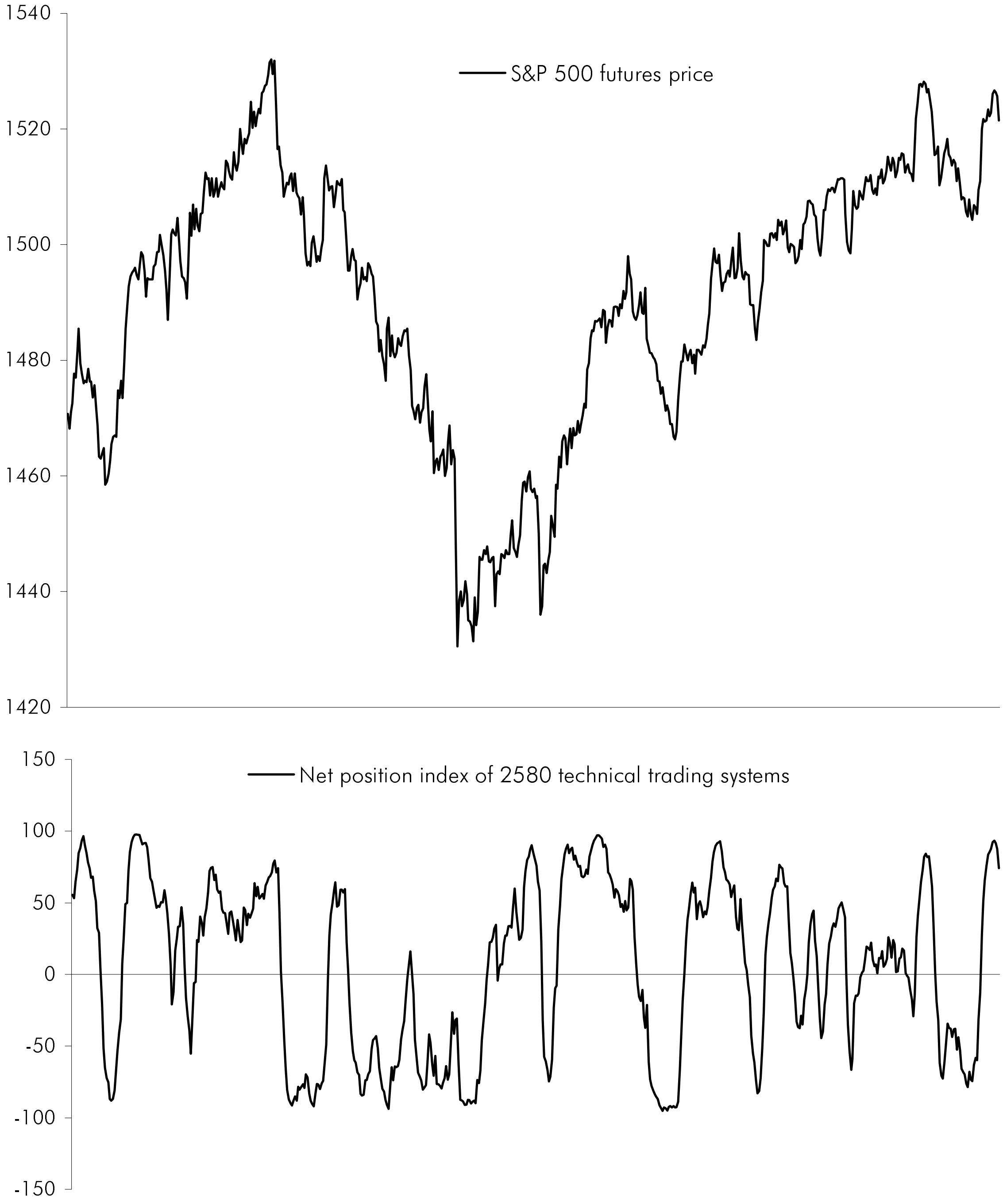
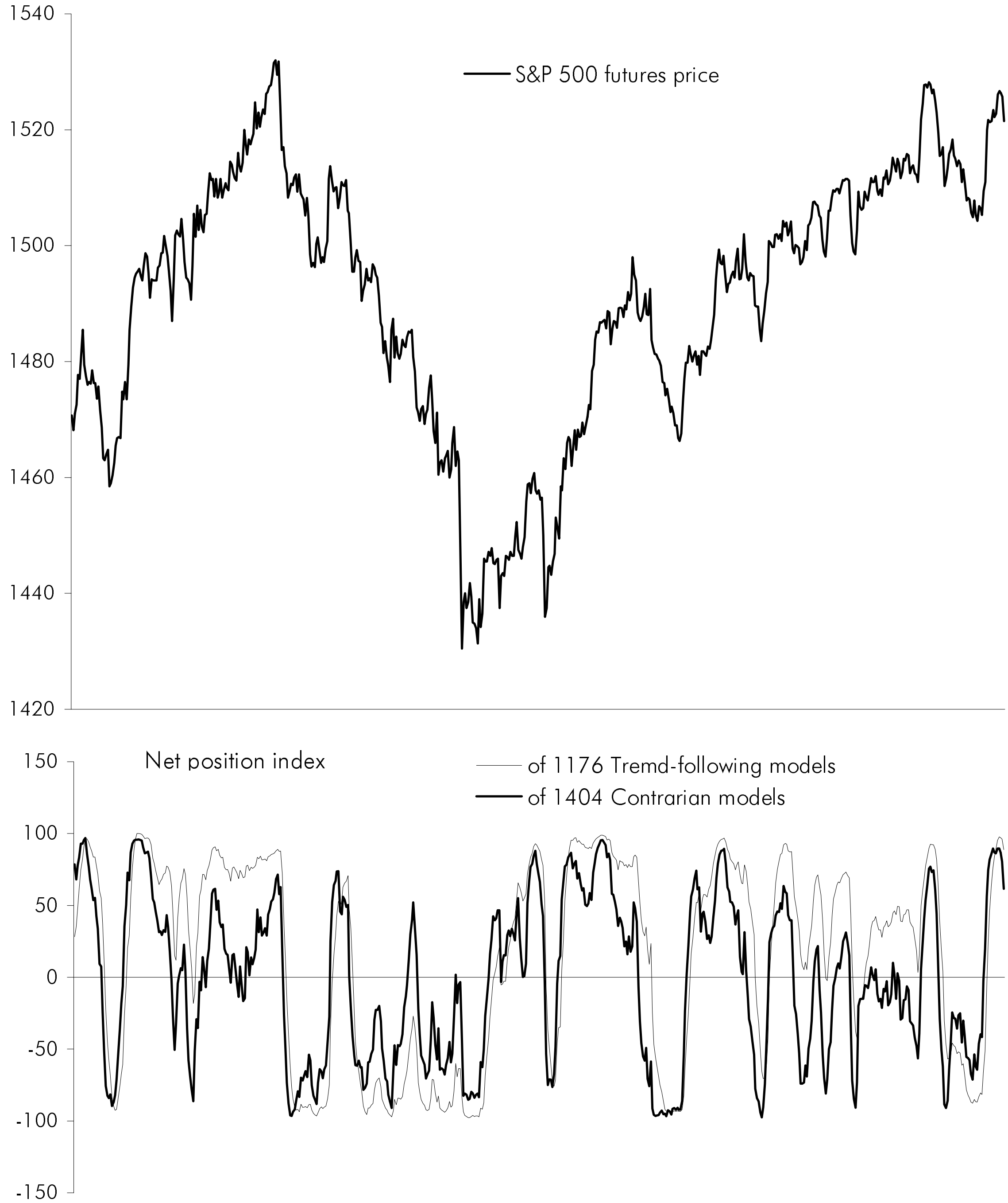


Figure 23a: Aggregate trading signals of momentum and contrarian models and stock price dynamics



8.2 Similarities in position taking of technical models

Figure 22a shows the gradual adjustment of the 2580 technical models to stock price movements, using S&P 500 trading during July and August 2000 as example. Due to a steep downward run between July 4, and July 6, almost all models change their positions from long to short. The strong though frequently interrupted upward movement of S&P 500 futures prices between July 6, and 17 (see also table 3a), cause roughly 75% of the models to hold long positions most of the time (the position index mostly exceeds 50). The opposite is true during the downward movement of stock futures prices which takes place over the second half of July. The fall of prices is so strong that roughly 90% of all models hold short position over this period (the position index lies mostly below 90).

Figure 22b displays a similar relationship between stock price movements and the aggregate position index of the models when trading DAX futures.

As has to be expected, the 1404 contrarian models react faster to changes in the direction of (persistent) stock price movements than the 1176 trend-following systems, e. g., the position index of the trend-following models lags behind the position index of the contrarian models (figures 23a and 23b).

The observations taken from figures 22a/b and 23a/b as well as from looking at the relationship between the movements of 30-minutes-stock-futures-prices and of the position index of the 2580 trading systems over different subperiods can be summarized as follows. First, most of the time the majority of the models are on the same side of the market, either long or short (the position index exceeds 50 in absolute terms most of the time). To put it differently: Time periods in which long and short positions are roughly in balance, which would cause the position index to oscillate around zero, seldom occur (one would expect those situations to prevail if stock prices actually followed a random walk). Second, the process of changing open positions in response to a new stock price rate trend usually takes off 1 to 3 trading intervals (e. g., 30-minutes-intervals in this case) after the local stock price maximum (minimum) has been reached. Third, it takes between 10 and 20 trading intervals (between 1 and 2 days) to gradually turn the positions of (almost) all models from short to long or long to short. Fourth, after all technical models have adjusted their open positions to the current trend, the trend often continues for some time (in such situations all models successfully exploit the trend).

Table 26a quantifies some of these observations. On 18.3% of all 30-minutes-intervals of the entire sample period more than 85% of the models hold a long position (PI>70), and on 16.1% of all intervals more than 85% of the models hold a short position (PI<-70). Hence, on 34.4% of all trading intervals more than 85% of the models hold the same – long or short – position. If one takes into account into account all trading intervals when the position index is higher than 50 (in absolute terms) one can conclude that on 53.5% of the entire sample period more than 75% of the models hold the same open position.

Table 26a: Distribution of time by positions and transactions of 2,580 technical trading systems S & P 500 futures trading based on 30-minutes-data

	Aggregate positions				
Net position index	Share in total Sample period in %	Mean of the net position index	Distribution by type of position		
			Long	Short	Neutral
> 70	18.29	85.22	88.86	– 3.64	7.51
50 - 70	9.97	60.15	70.63	– 10.48	18.89
30 - 50	9.62	40.06	56.84	– 16.78	26.37
10 - 30	9.46	19.98	44.27	– 24.30	31.43
–10 - 10	9.36	0.08	33.12	– 33.04	33.84
–30 - –10	8.94	– 19.96	24.03	– 43.98	31.99
–50 - –30	9.17	– 40.05	16.18	– 56.23	27.59
–70 - –50	9.05	– 60.09	9.75	– 69.84	20.41
< –70	16.14	– 85.43	3.46	– 88.88	7.66
Total	100.00	2.66	41.12	– 38.47	20.41

	Aggregate transactions			
	Share in total Sample period in %	Mean of the net transaction index	Distribution by type of transaction	
			Buy	Sell
> 70	0.01	81.38	81.38	0.00
50 - 70	0.09	56.33	56.47	– 0.14
30 - 50	1.30	35.84	36.18	– 0.34
10 - 30	15.55	16.49	17.61	– 1.12
–10 - 10	66.35	0.03	4.56	– 4.52
–30 - –10	15.14	– 16.56	1.13	– 17.69
–50 - –30	1.41	– 36.24	0.30	– 36.54
–70 - –50	0.13	– 57.76	0.12	– 57.88
< –70	0.02	– 76.37	0.00	– 76.37
Total	100.00	– 0.00	6.46	– 6.46

By contrast, periods during which short positions and long positions are roughly in balance seldom occur. The position index lies between 10 and –10 on only 9.4% of all trading intervals. These situations occur primarily during the change of the models from short to long positions and vice versa (graphically represented as realizations of the position index close to the 0-line). As has to be expected, the share of neutral positions reaches a maximum in these phases of technical trading (33.8% of the models hold neutral positions when the net positions index lies between 10 and –10).

On 66.4% of all 30-minutes-intervals less than 5% of the models execute buy or sell signals (the transaction index lies between 10 and –10). There are two reasons for that. First, the majority of the models hold the same – long or short – position for most of the time (little trading occurs during these periods, it concerns mainly fast models reacting to short-term stock price movements against the underlying trend). Second, the process of changing open positions from short to long and vice versa evolves only gradually. If this process is relatively slow then only 5% of the models or even less change their position on average. If this process is relatively fast then between 5% and 15% of the models change their position per trading interval: the transaction index lies between 10 and 30 (between -10 and -30) on 15.6% (15.1%) of all 30-minutes-intervals. Only on roughly 3% of all trading intervals is technical trading more intense in the sense that more than 15% of the models execute trading signals.

Table 26a shows also that the signals produced by technical models would cause their users trade very little with each other. If the models move relatively fast from short to long positions (10<TI<30) or vice versa (-10>TI>-30) then 15 times more buy (sell) transactions are carried out than sell (buy) transactions. On days when less than 5% of the models trade (10>TI>-10) roughly the same number of buys and sells are executed, however, their size is rather small (both gross transaction indices, the buy as well as the sell index amount to roughly 4.6 which implies that only 2.3% of all models trade with each other on average).

The taking and holding of open positions of the 2580 models is even more similar when trading DAX futures as compared to S&P 500 futures (figures 22b and 23b and table 26b). On 47.1% (64.7%) of all 30-minutes-intervals more than 85% (75%) of the models hold the same - long or short - position (S&P 500: 34.4%, and 53.5%, respectively). On 65.2% of all 30-minutes-intervals less than 5% of the models execute buy or sell signals in the DAX market (S&P 500 market: 66.4%). During these periods only 2.2% of the models trade with each other on average.

Table 27a shows the similarity in the trading behavior of different classes of technical models. The position holding of unstable models is more similar as compared to stable models. E. g., more than 80% of the models hold the same - long or short - position on 53.2% of all days in the case of unstable models but on only 42.7% in the case of stable models. The trading behavior of technical models does not differ significantly by the duration of profitable positions. Position holding of trend-following models is more similar as compared to contrarian models. E. g., more than 80% of contrarian models hold the same open position on 43.5% of all trading intervals, however, in the case of trend-following models this is true on 55.5% of all intervals.

Table 27a: Similarity of different types of technical trading systems in holding open positions
S & P 500 futures trading based on 30-minutes-data

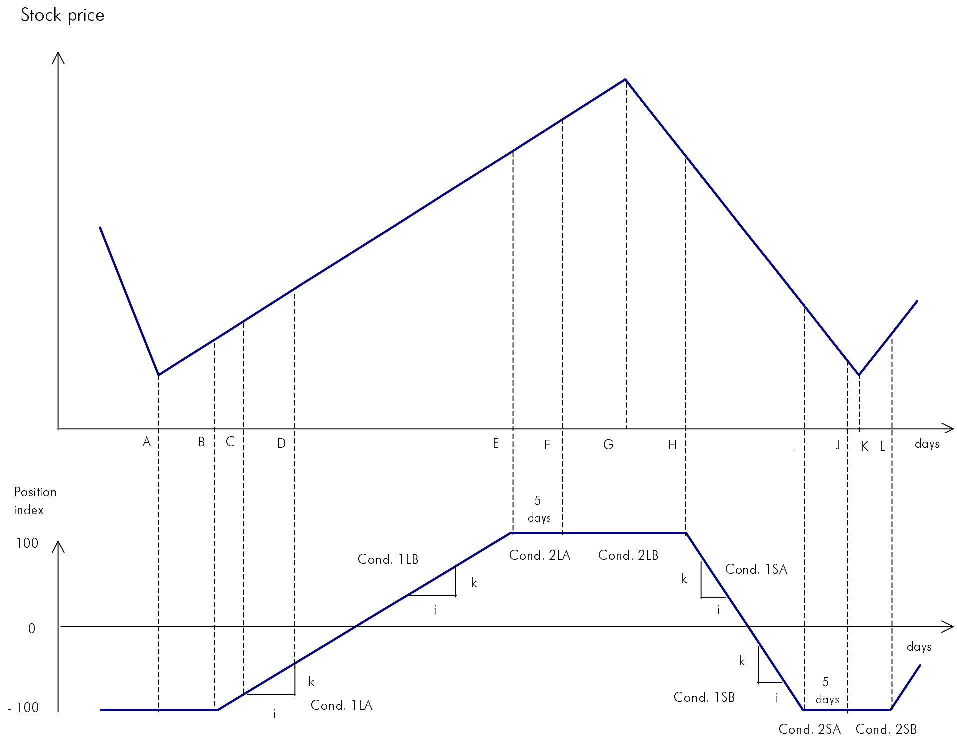
	Relative share of models holding the same – long or short – position		
	More than 90% (|PI| > 80)	More than 80% (|PI| > 60)	More than 70% (|PI| > 40)
	Share in total sample period in %		
Types of models			
By stability			
Stable	23.41	42.66	61.56
Unstable	32.19	53.20	70.45
By duration of profitable positions			
Short-term	32.89	50.73	66.74
Medium-term	29.92	50.75	68.07
Long-term	29.16	49.54	67.62
By type of trading strategy			
Trend-following	35.66	55.51	71.97
Contrarian	21.81	43.50	63.74
All models	23.59	44.11	62.96

The pattern of position holdings of the 2580 models is even more similar when trading DAX futures as compared to S&P 500 futures (table 27b).

8.3 The interaction between technical stock futures trading and stock price movements

As has been demonstrated, the profitability of technical stock futures trading based on 30-minutes-prices stems exclusively from the exploitation of persistent short-term trends (runs) around which stock prices fluctuate. It has also been shown that the aggregate technical models often produce a sequence of either buy or sell signals when they are trading and that the majority of the models holds the same – long or short – position most of the time when they are not trading (in other words, technical models rarely trade with each other). Hence, technical trading exerts an excess demand (supply) on stock price formation. It is therefore interesting to explore the interaction between the aggregate trading behavior of a great variety of different models and stock price dynamics. On one hand, technical models react to persistent upward (downward) price movements by producing a series of buy (sell) signals, on the other hand, the execution of these signals might strengthen the persistence of stock price runs.

Figure 24: Stock price trends and aggregate positions of technical models



As a first step the possible interactions between the aggregate trading behavior of technical models and the development of a stock price trend shall be discussed in a stylized manner. Thereby an upward trend is taken as example and three phases of the trend are distinguished according to the positions held by technical models (for simplicity, the following presentation assumes that technical trading is based on daily prices days, however, the stylized relationship between trading behavior of technical models and price dynamics applies to any kind of trading interval like 30-minutes-intervals).

The first phase of an upward trend (marked by the days A and B in figure 24) is usually caused by the excess demand of non-technical traders since technical trading systems seldom produce sell signals during an upward run (even the contrarian models change open positions usually only in response to a change in the direction of price movements, albeit before the new price movement has become a persistent trend). In most cases this additional demand will be triggered off by some economic or political news (e. g., an unexpected reduction of interest rates by the central bank) which lets news-based traders expect a rise of stock prices and, hence, induce them to open long dollar positions.

Over the second phase of an upward trend (between day B and day E in figure 24) technical models produce a sequence of buy signals, the fastest models at first, the slowest models at last. The execution of the technical trading signals then contribute to the prolongation of the trend. However, this feed-back effect is not sufficiently strong by itself to keep the process going since there are many other traders whose aggregate transactions impact upon stock price movements. If, e. g., new information causes (most) news-based traders to switch their positions from long to short then this will turn the price movement from upward to downward (figures 22a/b and 23a/b demonstrate that the position index increases frequently over some 30-minute-intervals from its minimum but then falls back again; in these cases the models which switch from a short to a long position and then go short again produce losses). In many cases, however, technical as well as non-technical traders continue to change their positions from short to long thereby strengthening the upward price movement (the reinforcing interaction between persistent stock price movements and the switching of technical models between long and short positions is depicted in figures 22a/b and 23a/b by those situations where the net position index moves gradually between -100 to +100).

Over the third phase of an upward price trend most or even all technical models hold long positions (marked by the days E and G in figure 24). In many cases the trend continues for some time during this phase (figures 22a/b). The longer the trend lasts the more models make profits from the exploitation of the trend. Since technical models already hold a long position the prolongation of an upward trend is caused by an additional demand of non-technical traders (however, the fact that – almost - all technical models hold a long position might foster the prolongation of the trend). This additional demand might stem from (amateur) "bandwagonists" who jump later on price trends than technical traders or from news-based traders. The transactions of the latter will strengthen the upward movement the more the market "mood" is bullish. If such an expectational bias prevails traders undervalue (or even disregard) news which contradict the bias and overvalue news which confirm the bias. E. g., during the last phase of the bull market of the 1990s stock prices almost did not react to negative news like negative earnings reports (this holds particularly true for stocks of the New Economy), however, stock prices did react strongly to positive news like a higher than expected economic growth which seemed to confirm the expectation of a prolongation of the bull market.

The longer an stock price run lasts the greater becomes the probability that it ends. This is so for at least three reasons. First, the number of traders who get on the bandwagon declines. Second, the incentive to cash in profits from holding open positions in line with the (short-term) trend becomes progressively larger. Third, more and more (non-technical) contrarian traders consider the dollar overbought (oversold) and, hence, open a short (long) position in order to profit from the expected reversal of the trend.

When the stock price run finally comes to an end, mostly triggered off by some economic or political news, a countermovement is almost always triggered off (figures 22a/b). With some lag technical models – first contrarian and then trend-following models - start to close the former positions and open new counterpositions (between day G and day H in figure 24).

For technical stock trading to be overall profitable it is necessary that (short-term) trends continue for some time (e. g., over some hours in the case of technical trading based on 30-minutes-prices) after the models have taken long (short) positions. This is so for three reasons. First, all models have to be compensated for the single losses they incur during "whipsaws". Second, fast models often make losses during an "underlying" stock price run since they react to (very) short-lasting countermovements. Third, slow models open a long (short) position only at a relatively late stage of an upward (downward) run so that they can exploit the run successfully only if it continues for some time.

In order to estimate how close stock price movements and the trading behavior of technical models are related to each other the following exercise has been carried out. At first, some conditions concerning the change and the level of the net position index are specified. These conditions grasp typical configurations in the aggregate trading behavior of technical models. Then, the difference of the means of the stock price changes observed under these conditions from their unconditional means over the entire sample is evaluated.

The first type of conditions concerns the speed at which technical models switch their open positions from short to long (condition 1L) or from long to short (condition 1S). Condition 1L comprises all cases where 10% (20%, 40%) of all models have been moving from short to long positions over the past 3 (5, 10) 30-minutes-intervals in such a way that the position index (PI) increases monotonically. In addition the condition 1L excludes all cases where more than 90% of the models hold long positions (these cases are comprised by condition 2L).

More formally condition 1L is defined as follows.

Condition 1L: $[PI_t - PI_{t-i}] > k \cap [PI_{t-n} - PI_{t-n-1}] \geq 0 \cap [PI_t \leq 80]$

k = 20, 40, 80

i = 3, 5, 10

n = 0, 1, ... (i-1)

Condition 1S comprises the analogous cases of changes positions from long to short.

Condition 1S: $[PI_t - PI_{t-i}] < -k \cap [PI_{t-n} - PI_{t-n-1}] \leq 0 \cap [PI_t \geq -80]$

k = 20, 40, 80

I = 3, 5, 10

n = 0, 1, ... (i-1)

Condition 2L(S) comprises all cases where more than 90% of all models hold long (short) positions:[23])

Condition 2L(S): PI > 80 (PI < 80)

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[23]) Situations where the position holding of technical models is concentrated on one side of the market are defined as all cases where the position index exceeds 80 or lies below –80. These values were used instead of 100 and –100, respectively, for the following reason. This study includes also very "fast" models, e. g., models which are extremely sensitive to stock price changes (the "fastest" like momentum and RSIN models with a time span of only three 30-minutes-intervals produce more than 1000 trading signals per year). These models are most probably not used in practice, however, in order to avoid the suspicion of "model mining" they were not excluded from the analysis. Hence, situations where only these models go short (long) for a few trading intervals whereas all other models keep holding long (short) positions should still be considered typical of one-sided position holding of technical trading systems.

The diagram gives a graphical representation of the meaning of these four conditions (the subdivision of the conditions 1 and 2, marked by "A" and "B", will be discussed later).

For each trading interval t on which these conditions are fulfilled the rate of change (CSP_t) between the current stock futures price (SP_t) and the respective price j periods (SP_{t+j}) ahead is calculated (j...5, 10, 20, 40). Then the means over the conditional stock price changes are compared to the unconditional means over the entire sample and the significance of the differences is estimated using the t-statistic. This comparison shall examine if and to what extent stock futures prices continue to rise (fall) after 10% (20%, 40%) of technical models have changed their position from short (long) to long (short), and if and to what extent this is the case when 90% of all models hold long (short) positions.

For each trading period on which condition 1 is fulfilled also the stock futures price changes over the past i days are calculated and compared to the unconditional price changes. The purpose of this exercise is to estimate the strength of the interaction between stock price movements and the simultaneous execution of technical trading signals induced by these movements.

Table 28a shows that the conditions 1 are rather frequently fulfilled (S&P trading). E. g., in 11116 (10863) cases more than 10% of all models change their open positions from short to long (from long to short) within 3 periods of 30 minutes (conditions 1L(S) with k=20 and i=3, abbreviated as condition 1L(S)[20/3)]). In 7683 (7263) cases more than 20% of the models change their open position in the same direction within 5 periods. Conditions 1L(S)[80/10] are realized in only 4307 (3969) cases. The number of cases fulfilling conditions 1 are the smaller the larger is the parameter k. E. g., if k=80 then the possible realizations of condition 1L are restricted to a range of the position index between -20 and 90, however, if k=20 then condition 1L could be fulfilled within a range of the position index between -80 and 90.

Conditions 2 occur less frequently than conditions 1 when trading S&P 500 futures (except for conditions 1L(S)[80/10]). In 7801 cases more than 90% of all models hold a long position (condition 2L). Since S&P 500 futures prices were rising over the entire sample period, condition 2S was less frequently realized (6959 cases).

Despite the different restrictions imposed on conditions 1L(S) and 2L(S) either of them is fulfilled on 36739 trading intervals out of the entire sample of 62727 trading periods (in order to avoid doublecounting only the cases of conditions 1L(S)[20/3] are considered as regards condition 1 – most cases satisfying condition 1 with k=40 or k=80 are a subset of the cases satisfying condition 1 with k=20).

In the case of DAX futures trading one of these four conditions is satisfied on 12236 trading intervals out of 17688 possible cases (table 28b). Hence, the relative share of 30-minute-intervals on which one of the conditions 1L(S)[20/3] and 2L(S) holds true in the entire sample is higher in the DAX market as compared to the S&P 500 market (69.2% and 58.6%, respectively). The fact that one of the conditions 1L(S) and 2L(S) is fulfilled during most of the trading intervals implies a systematic pattern in the aggregate trading behavior of technical models which can hardly be reconciled with the assumption that stock futures prices follow a random walk.

The means of the stock index futures price changes (CSP_t) at all points in time satisfying conditions 1 over the <u>past</u> 3 (5,10) 30-minutes-intervals are very much higher than the unconditional means over the entire sample period (at the same time S&P 500 futures prices move in the same direction as the position index). E. g., the average (relative) S&P 500 futures price change over 5 consecutive 30-minutes-intervals amounts to 0.015% between 1983 and 2000, however, when 20% of the technical models turn their open position from short to long within 5 intervals the S&P 500 futures price increases on average by 0.63%. This highly significant difference (t-statistic: 85.9) can be explained as the result of the interaction between stock futures price movements and the (thereby induced) changes of open positions by technical models.

Table 28a: Aggregate trading signals of 2,580 technical models and stock price movements
S & P 500 futures trading based on 30-minutes-data

Parameters of the conditions for CSP		Time span J of CSP	More than 10% (20%, 40%) of all models change open positions in the same direction within 3 (5, 10) 30-minutes-intervals					
k	i		From short to long positions (condition 1L)			From long to short positions (condition 1S)		
			Number of cases	Mean of CSP_{t+i}	t-statistic	Number of cases	Mean of CSP_{t+i}	t-statistic
20	3	–3	11116	0.422	92.95	10863	– 0.395	– 90.03
		5	11116	0.044	4.79	10863	– 0.008	– 3.58
		10	11116	0.069	4.23	10863	– 0.010	– 4.58
		20	11116	0.078	1.43	10863	0.041	– 1.50
		40	11116	0.154	2.02	10863	0.070	– 2.65
40	5	–5	7683	0.632	85.86	7263	– 0.580	– 92.55
		5	7683	0.049	4.60	7263	– 0.007	– 2.79
		10	7683	0.073	3.97	7263	– 0.010	– 3.80
		20	7683	0.092	2.18	7263	0.051	– 0.54
		40	7683	0.164	2.31	7263	0.072	– 2.11
80	10	–10	4307	0.916	59.27	3969	– 0.782	– 101.43
		5	4307	0.052	4.26	3969	– 0.003	– 1.89
		10	4307	0.056	1.80	3969	0.018	– 0.87
		20	4307	0.110	2.63	3969	0.048	– 0.58
		40	4307	0.158	1.50	3969	0.064	– 1.83
			More than 90% of all models hold the same type of open position					
			Long positions (condition 2L)			Short positions (condition 2S)		
		5	7801	0.053	4.77	6959	– 0.033	– 3.72
		10	7801	0.067	3.56	6959	– 0.012	– 2.21
		20	7801	0.079	1.36	6959	0.074	0.57
		40	7801	0.066	– 2.57	6959	0.228	3.48

The table presents the means of changes over i business days (CSP_{t+i}) under four different conditions.

Condition 1L (S) comprises all situations where more than 10% (20%, 40%) of all trading systems have been moving monotonically from short to long (long to short) positions over the past 3 (5, 10) trading intervals. The moves are restricted to a range of the position index PI_t between 80 and –80.

Condition 2L (S) comprises all situations beyond this range, i.e., where more than 90% of all trading systems hold long (short) positions. More formally these conditions are defined as follows:

Condition 1L (S): $[PI_t - PI_{t-1}] > k \ (< -k) \cap [PI_{t-n} - PI_{t-n-1}] \geq 0 \leq = 0 \cap [-80 \leq PI_t \leq 80]$

k 20, 40, 80
i 3, 5, 10
n .... 0, 1, ... (i – 1)

Condition 2L (S): PI > 80 (< – 80)

$CSP_{t+j} = 100 * [SP_{t+j} - SP_t] / SP_t$ for j 5, 10, 20, 40
$CSP_{t+j} = 100 * [SP_t - SP_{t+j}] / SP_t$ for j .... –5

The t-statistic tests for the significance of the difference between the mean of the conditional exchange rate changes and the unconditional mean over the entire sample, the latter being as follows (S.D. in parentheses):

For j = 3 0.0090 (0.5155)
5 0.0149 (0.6517)
10 0.0297 (0.9319)
20 0.0593 (1.3144)
40 0.1171 (1.7885)

If one looks at all cases when technical models change their positions at a certain speed (as defined by the parameters k and i of condition 1) across different classes of models in both stock futures markets, two observations can be made with respect to the simultaneous stock price changes (see all lines in the tables 28a/b to 30a/b where the time span j of CSP_t is negative). First, stock index futures prices move on average strongly in the direction congruent with the simultaneous transactions of technical stock futures trading. Second, the means of the conditional (ex-post) stock index changes differ significantly from the unconditional means (the t-statistics exceed 50 in most cases). However, since stock futures price movements and technical position taking interact simultaneously one cannot separate that part of the (ex-post) conditional price changes which causes technical models to produce trading signals from that part which is caused by the execution of the technical trading signals.

The means of stock futures price changes over the 5 (10, 20, 40) 30-minutes-intervals following the realization of condition 1 has mostly the same sign as the preceding change in the position index (tables 28a and 28b). This holds true in all cases of changing positions from short to long induced by and strengthening the upward movements of stock prices (conditions 1L). In 15 out of 24 cases stock futures prices rise on average subsequent to realizations of condition 1S, i.e., after a certain share of models has changed positions from long to short. However, in 7 of these cases (4 concerning the S&P 500 futures market and 3 concerning the DAX futures market) the means of the conditional ex-ante price changes are still significantly smaller than the unconditional means (stock futures prices rise in these cases less than on average over the entire sample period).

The means of the conditional ex-ante stock futures price changes are in most cases (conditions 1) significantly different from the unconditional means albeit to a much lesser extent than the means of the conditional ex-post price changes. The t-statistics testing the significance of the difference between the means of the conditional ex-ante stock price changes and the unconditional means exceed 1.8 (and have the right sign at the same time) in 29 out of 48 cases (tables 28a and 28b). However, the t-statistics differ remarkably across the time span j of the ex-ante stock price changes. The means of the price changes over the 5 and 10 trading intervals following the realization of condition 1 have in most cases the right sign and are at the same time significantly different from the unconditional means. Over a time horizon of 20 and 40 intervals of 30 minutes (between 1 1/2 and 3 business days in the case of S&P 500 futures trading), by contrast, this holds true in only 12 out of 24 cases.

The main reason for this difference lies in the fact that persistent stock price runs on the basis of 30-minutes-data last in most cases very short. For the same reason short-term models perform in general better when stock futures trading is based on 30-minutes-prices than medium-term and long-term models.

After those 30-minutes-intervals during which 90% of all models hold already a long (short) position (conditions 2) stock futures prices continue to rise (fall) sufficiently often so that the conditional means of the ex-ante price changes are significantly higher (in absolute terms) than the unconditional means over the entire sample period (tables 28a and 28b). This difference as measured by the t-statistic is roughly as great as in the case of conditions 1 when looking at the price changes over 5 and 10 intervals of 30 minutes following the realization of condition 2. However, over time spans of 20 and 40 trading intervals the means of the conditional (ex-ante) price changes are insignificantly different from the unconditional means or have even the wrong sign. In the case of S&P 500 futures trading, e. g., prices fall (rise) over the 40 intervals following the realization of condition 2L(S) significantly stronger than on average over the entire sample period. This relationship implies that 30-minutes-prices of stock index futures are mean-reverting over relatively short time horizons. This observation contributes to a better understanding of two findings of the profitability tests based on 30-minutes-data, namely, that short term trading systems perform best, and that contrarian models perform better than trend-following models.

Tables 29a and 29b present the results of the statistical analysis of the relationship between the trading behavior of different classes of technical models according to conditions 1 and 2 and stock futures price movements before and after the realizations of both conditions. The models are classified according to the type of trading rule (trend-following and contrarian systems) as well as to the average duration of profitable positions (short-term, medium-term and long-term models based on the cluster analysis). Condition 1 is used only with k=40 and i=5, the ex-ante stock futures price changes are restricted to a time span of 10 and 20 trading intervals, respectively. The main results do not differ from those obtained for all 2580 models (tables 28a and 28b). However, the following additional observations are worth mentioning.

Table 29a: Aggregate trading signals produced by different types of technical models and stock price movements
S & P 500 futures trading based on 30-minutes-data

Types of models	Time span j of CSP_{t+j}	More than 20% of all models change open positions in the same direction within five 30-minutes intervals (K = 40, i = 5, –80 ≥ PI ≤ 80)					
		From short to long positions (condition 1L)			From long to short positions (condition 1S)		
		Number of cases	Mean of CSP_{t+j}	t-statistic	Number of cases	Mean of CSP_{t+j}	t-statistic
Trend-following	– 5	6966	0.596	79.60	6883	– 0.559	– 83.51
	10	6966	0.078	4.19	6883	0.002	– 2.63
	20	6966	0.103	2.78	6883	0.045	– 0.93
Contrarian	– 5	8249	0.599	84.12	7712	– 0.527	– 88.11
	10	8249	0.074	4.13	7712	– 0.014	– 4.32
	20	8249	0.084	1.72	7712	0.051	– 0.61
Short-term	– 5	8630	0.190	30.23	8674	– 0.152	– 43.53
	10	8630	0.054	2.39	8674	– 0.014	– 4.63
	20	8630	0.061	0.13	8674	0.037	– 1.63
Medium-term	– 5	7631	0.499	63.97	7421	– 0.419	– 84.85
	10	7631	0.080	4.55	7421	– 0.024	– 5.31
	20	7631	0.077	1.15	7421	0.038	– 1.46
Long-term	– 5	7431	0.511	69.71	7226	– 0.474	– 75.75
	10	7431	0.048	1.73	7226	0.002	– 2.81
	20	7431	0.081	1.45	7226	0.034	– 1.73
		More than 90% of alll models hold the same type of open position					
		Long positions (condition 2L: PI > 80)			Short positions (condition 2S: PI < –80)		
		Number of cases	Mean of CSP_{t+j}	t-statistic	Number of cases	Mean of CSP_{t+j}	t-statistic
Trend-following	10	12387	0.032	0.32	9974	0.036	0.46
	20	12387	0.054	– 0.43	9974	0.119	2.95
Contrarian	10	6723	0.094	5.66	6957	– 0.029	– 3.26
	20	6723	0.100	2.66	6957	0.049	– 0.40
Short-term	10	10783	0.102	7.92	9846	– 0.036	– 5.20
	20	10783	0.096	2.94	9846	0.046	– 0.75
Medium-term	10	9969	0.078	5.25	8795	– 0.024	– 3.57
	20	9969	0.081	1.69	8795	0.070	0.50
Long-term	10	9563	0.039	0.94	8723	0.028	– 0.08
	20	9563	0.064	0.38	8723	0.106	2.15

For a definition of the conditions 1L (S) and for the conditions 2L (S) see Table 28a.

The t-statistic tests for the significance of the difference between the mean of the conditional exchange rate changes and the unconditional mean over the entire sample, the latter being as follows (S.D. in parentheses):
For j = 5 0.0149 (0.6517)
10 0.0297 (0.9319)
20 0.0593 (1.3144)

First, trend-following models realize condition 1 (e. g., 20% of the models change their open position in the same direction within 5 trading intervals) less frequently than contrarian models (13849 and 15961 cases, respectively, when trading S&P 500 futures). Second, the means of stock price changes over 10 trading intervals following the realization of conditions 1 differ from the unconditional means more significantly in the case of contrarian models as compared to trend-following models. Third, this difference between contrarian and trend-following models is even more pronounced as regards stock futures price changes following the realization of condition 2. Fourth, trend-following models are more frequently on the same side of the market (condition 2) as compared to contrarian models. Fifth, the phenomenon that stock prices continue to rise (fall) after technical trading systems have realized conditions 2 is most pronounced in the case of short-term models, followed by medium-term models and long-term models (the average profitability of these types of models follows the same ranking).

Finally, the following exercise has been carried out. Each of the four phases of technical trading as defined by the conditions 1L(S) and 2L(S) is divided into two subphases by the (additional) conditions A and B (the parameters of condition 1 are set at k=40 and i=5). The meaning of the (sub)conditions A and B is explained as follows, taking an upward trend as example.

Condition 1LA comprises all cases where 20% of all models have changed their positions from long to short and where at the same time still less than 50% of the models hold long positions. Hence, condition 1LA covers the first phase of reversing technical positions after the stock futures prices have started to rise (all cases under condition 1LA lie below the zero level of the position index – see figure 24).

Condition 1LB comprises the second phase of position changes, e. g., when the stock futures price run has gained momentum so that already more that 50% of the models are holding long positions.

Condition 2LA covers the third phase in the trading behavior of technical models during an upward trend, namely, the first 5 30-minutes-intervals after more than 90% of all models have opened and are still holding long positions.

Condition 2LB comprises the other 30-minutes-intervals over which 90% of all models keep holding long positions, i.e., the fourth and last phase which endures until the models start to again reverse their position in reaction to a downward movement.

Figure 24 illustrates the meaning of these eight conditions which correspond to eight (stylized) phases of technical trading (whenever stock price movements develop to persistent upward and downward trends).

When trading S&P 500 futures condition 1LA is much less frequently realized than condition 1SB, the opposite is true as regards conditions 1LB and 1SB (the number of realizations of conditions 1L and 1S is roughly the same – table 30a). These differences might be due to the fact that stock prices strongly increased over the sample period. This increase could have been realized in such a way that upward movements lasted longer than downward movements, the latter being at the same time steeper than the former (such a pattern was typical for the appreciation process of the dollar exchange rate between 1980 and 1985 – Schulmeister, 1987 and 1988).

Table 30a shows that the size of the conditional ex-ante stock futures price changes differs across the four conditions 1LA, 1LB, 2LA and 2LB (e. g., in the case of an upward trend). The average rise of the S&P 500 futures price following the realizations of condition 1LA, is significantly higher than the unconditional price changes over all 4 time spans. The increase of S&P 500 futures prices under condition 1LB is in most cases smaller than under condition 1LA (price movements often loose persistence after a first "take-off"). The average rise of S&P 500 futures prices is most significantly different from the unconditional mean following the realizations of condition 2LA, e. g., after 90% of all models have taken long positions due to a continuation of the stock price run (only over a time span of 40 intervals does this not hold true). Stock price changes subsequent to the realizations of condition 2LB are smallest and often even significantly negative (stock futures price changes between period (t) and period (t+10) or (t+20) will often be negative if period (t) belongs to the last phase of an upward trend; this effect is strengthened if the upward movement is followed by a downward trend – see figure 24). As a consequence, the means of the conditional ex-ante stock futures price changes differ most significantly from the unconditional means in the cases of condition 2LA.

Table 30a: Eight phases of technical trading and stock price movements
All models
S & P 500 futures trading based on 30-minutes-data

Conditions for CSP_{t+j} (= Phase of technical trading)	Time span j of CSP_{t+j}	(Increasing) Long positions (conditions .L.)			(Increasing) Short positions (conditions .S.)		
		Number of cases	Mean of CSP_{t+j}	t-statistics	Number of cases	Mean of CSP_{t+j}	t-statistics
1A	– 5	1972	0.609	34.81	5327	– 0.611	– 93.65
	5	1972	0.047	1.88	5327	– 0.016	– 3.83
1B	– 5	5711	0.641	84.95	1936	– 0.496	– 35.97
	5	5711	0.049	4.52	1936	0.018	0.16
2A	5	6157	0.073	6.23	5666	– 0.049	– 6.01
2B	5	1644	– 0.020	– 2.57	1293	0.038	0.47
1A	10	1972	0.105	3.38	5327	– 0.016	– 3.96
1B	10	5711	0.062	2.66	1936	0.006	– 1.09
2A	10	6157	0.095	5.39	5666	– 0.049	– 5.09
2B	10	1644	– 0.036	– 3.58	1293	0.153	1.68
1A	20	1972	0.133	2.43	5327	0.048	– 0.65
1B	20	5711	0.078	1.11	1936	0.060	0.01
2A	20	6157	0.117	3.61	5666	– 0.003	– 2.63
2B	20	1644	– 0.065	– 4.53	1293	0.410	3.86
1A	40	1972	0.226	2.65	5327	0.088	– 1.16
1B	40	5711	0.143	1.13	1936	0.027	– 2.35
2A	40	6157	0.076	– 1.83	5666	0.137	0.62
2B	40	1644	0.030	– 2.39	1293	0.624	5.73

Each of the four phases of technical trading defined by the conditions 1L (S) and the conditions 2L (S) for k = 40 and i = 5 (see Table 28a) is divided into two subphases by the conditions A and B:

Condition 1L (S): More than 20% of all trading systems have been moving from short to long (long to short) positions over the past five 30-minutes-intervals within the range $\{-80 \leq PI_t \leq 80\}$ and ....

Condition 1L (S) A: Less than 50% of the models hold long (short) positions, i.e., $PI_t \leq 0$ ($PI_t \geq 0$).

Condition 1L (S) B: More than 50% of the models holg long (short) positions, i.e., $PI_t \geq 0$ ($PI_t \leq 0$).

Condition 2L (S): More than 90% of all trading systems hold long (short) positions, i.e., $PI_t > 80$ ($PI_t < -80$).

Condition 2L (S) A: Comprises the first five 30-minutes-intervals for which condition 2L (S) holds true.

Condition 2L (S) B: Comprises the other 30-minutes-intervals for which condition 2L (S) holds true.

The t-statistics tests for the significance of the difference between the mean of the conditional stock price changes and the unconditional mean over the entire sample, the latter being als follows (S.D. in parentheses):

For j = 5 0.0149 (0.6517)
10 0.0297 (0.9319)
20 0.0593 (1.3144)
40 0.1171 (1.7885)

These results also hold true for the conditional ex-ante stock futures price changes in the case of downward trends (conditions 1SA, 1SB, 2SA and 2SB). Trend reversals after downward movements seem to be even more pronounced as compared to trend–reversals following upward trends. E. g., S&P 500 futures prices rise on average over 20 and 40 half-hour-intervals following the realization of condition 2SB to a greater extent than they fall following condition 2LB (table 30a). This difference is most probably related to the fact that S&P 500 futures prices strongly increased over the entire sample period.

The relationships between the trading behavior of technical models in the S&P 500 market and (subsequent) stock price movements also hold true for price changes over 10 and 20 trading intervals the case of the DAX futures market (table 30b).

The three most important observations concerning the interaction between stock futures price movements and the aggregate trading behavior of technical models can be summarized as follows.

First, over those periods over which technical models change their open positions at a certain speed (according to condition 1) stock futures prices move in the direction congruent with the transactions of the technical models. At the same time the means of these conditional ex-post price changes are very much higher than on average over the entire sample period. This observation reflects the strong and simultaneous feed-back between stock futures price movements and the transactions triggered off by technical models. Second, the means of stock futures price changes taking place over 5 or10 half-hour-intervals after a certain part of technical models has reversed open positions at a certain speed (according to conditions 1) have mostly the same sign as the preceding change in the position index and are usually significantly higher (in absolute terms) than the unconditional means over the entire sample period. Third, this holds to an even higher extent true for stock futures price changes following the first 5 half-hours-intervals when 90% of the models hold the same – long or short – position (conditions 2A). Fourth, subsequent to the other intervals during which 90% of the models hold the same long (short) position (conditions 2B) stock futures prices fall (rise) on average. This phenomenon reflects the frequent occurrence of trend-reversals of stock futures prices.

These observations reflect the finding of this study that almost all tested technical models produce excess returns over the entire sample period in the S&P 500 as well as in the DAX futures market due to profitable positions lasting longer than unprofitable positions. One can therefore conclude that the frequent occurrence of persistent though short-term stock futures price trends on the basis of 30-minutes-data accounts for two important results of this study. First, stock futures price trends exclusively account for the overall profitability of 98.7% (S&P 500) and 97.6% (DAX) of the 2580 technical models in both markets. Second, stock futures price trends on the basis of 30-minutes-data last sufficiently often so long that most technical models gradually reverse their open positions and keep holding the new positions for some time.

Three factors might contribute most to the frequent occurrence of persistent stock price trends on the basis of 30-minutes-data and the related aggregate trading behavior of technical models. First, stock price movements and the transactions of technical models reinforce each other ("ceteris paribus") due to the feed-back effects already discussed. Second, most of the time there prevails a market "mood" causing medium-term expectations to be biased upward or downward. If, e. g., the market is "bullish" news-based traders will react much stronger to news which confirm the expectation of a rising stock prices than to news which contradict this expectation. In addition, all types of traders might in this case put more money into a long stock (futures) position than into a short position (and vice versa if the market is "bearish"). Third, non-technical "bandwagonists" join the stock price trend, some of them at an early stage of the trend (once it has gained momentum), some of them – possibly amateur speculators – relatively late. That phenomenon which is most essential for the overall profitability of technical stock (futures) trading, namely, that the stock prices continue to rise (fall) after almost all technical models already have opened long (short) positions, can most plausibly be attributed to the effects of persistent market "moods" and of the related "bandwagon trading".

9. Summary and evaluation of the results

In this final section, the main results of the study will be summarized and evaluated in the context of the basic assumptions of equilibrium economics and of the "noise trader approach." This evaluation will focus on the issues of expectations formation, market efficiency, stabilizing versus destabilizing speculation and profitable versus unprofitable speculation.[24])

9.1 The main results of the study

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

- The study simulates the performance of 2124 moving average models, 228 momentum models and 228 relative-strength-models the S&P 500 and in the DAX market based an daily data (spot and futures markets) as well as 30-minutes-data (futures markets only).

- Technical trading in the S&P 500 spot market based on daily prices would not have been markedly profitable over the period between 1960 and 2000. The 2580 models tested would have produced an average gross rate of return of only 1.9% per year (65.2% of the models would have been profitable).

- The models perform significantly better in the DAX spot market, producing an average gross rate of return of 8.6% per year (only 1.5% of the models are unprofitable).

- 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) to –5.1% (1992/2000).

- The 2580 models are even more unprofitable when trading S&P 500 futures contracts between 1983 and 2000, they produce an average gross rate of return of –5.9% per year (1992/2000: -6.7%).

- When trading DAX futures the models perform better producing an gross rate of return of 4.2% per year on average between 1992 and 2000.

- The picture is very different when stock futures trading is simulated on the basis of 30-minutes-data (the following remarks refer to the performance of futures trading based on 30-minutes-prices). When trading S&P 500 contracts the models produce a an

[24]) Since the results of this study are very similar to the results obtained from simulations of technical trading in the foreign exchange markets the evaluation draws heavily on Schulmeister (2000, chapter 6).

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%).

- The profitability of the models is much higher when trading DAX futures, they produce between 1997 and 2000 a gross and net rate of return of 23.2% and 17.1%, respectively.
- At an margin requirement of 10% of contract value the 2580 technical models would have produced a net rate of return per capital invested of 43% per year in the S&P 500 market (1983-2000) and of 171% per year in the DAX market (in practice, the net rate of return would have been higher than this estimate since margins are most of the time lower than 10% of contract value).
- The great majority of the models is profitable in both markets, only 1.3% (S&P 500) and 2.4% (DAX) of the 2580 models produce a negative gross rate of return.
- The probability of making an overall loss when strictly following one of these models was close to zero (the t-statistic testing the mean of the single returns against an hypothesized value of zero, exceeds 2.0 in almost all cases).
- The profitability of technical stock futures trading is exclusively due to the exploitation of persistent price trends around which stock prices fluctuate. This is reflected by the fact that profitable positions of technical models last on average several times longer than unprofitable positions. At the same time, unprofitable positions occur more frequently than profitable positions and the average loss per 30-minutes-interval during unprofitable positions is higher then the average profit per trading interval during profitable positions.
- These results do not change substantially when technical stock trading is simulated over 6 subperiods for S&P 500 trading (4 subperiods for DAX trading). In only 2499 out of 15480 cases (performance of 2580 models over 6 subperiods in the S&P 500 market) and in only 2015 out of 10320 cases (DAX market) did the technical models produce losses.

- The out-of-sample profitability of those models which performed best in sample (e. g., over the most recent subperiod) is significantly higher than the average in-sample-profitability of all models. In the case of S&P 500 futures trading the 25 models selected on the basis of their past performance produce an average gross rate of return of 18.7% over the subsequent periods (in the case of DAX trading the ex-ante-profitability amounts to 22.3%).

- If one aggregates transactions as well as open positions of all 2580 technical models, it turns out that they exert an excessive demand (supply) pressure on the stock markets. This is so for two reasons. First, when technical models produce trading signals they are either buying or selling (e. g., technical models using the same frequency of price data do not trade with each other). Second, when technical models maintain open positions most of them are on the same side of the market, either long or short.

- There is a strong feed-back mechanism operating between stock price movements and the transactions triggered off by technical models. Rising prices, for example, cause increasingly more technical models to produce buy signals, which in turn strengthen and lengthen the upward trend.

- After a certain proportion of technical models has changed their open positions from short to long (long to short) stock prices continue to rise (fall) over the subsequent five to ten 30-minutes-intervals. Thereafter, stock price trends tend to change their direction providing new profit opportunities for technical trading, in particular on the basis of contrarian models.

9.2 Performance and popularity of technical stock trading

The study has shown that persistent stock price runs occur sufficiently often on the basis of 30-minutes-data (and probably also on the basis of other intraday data frequencies) as to render almost all 2580 technical models profitable over the entire sample period. This result does, however, not imply that technical stock trading represents a "money machine". By contrast, 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 relative to the capital invested if stock (index) futures are traded (involving huge margin calls). Hence, if a private (amateur) investor happens to start technical trading before or during such a "whipsaws" period he/she might quickly be wiped out of the market. By contrast, a professional trader of a bank or an institutional investor can survive such a period more easily since usually more financial resources are disposable to a professional trader as compared to an amateur).

- Lack of financial resources might also prevent private technical traders from sticking to the selected model during "whipsaws" so that he/she would omit the profits from exploiting persistent price trends over the long run (frequent changes of the model in use can easily increase the overall loss).

- "Model mining" represents a particularly important source of risk of technical trading. If a 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. This risk is the higher the greater is the number of models and data frequencies tested, and the shorter is the test period. Whereas an experienced trader is usually aware of this risk an amateur might easily be impressed by the huge profits he/she would have earned had he/she followed some "exotic" model over the most recent months (over short periods of time extremely "fast" models like moving average models with a difference between MAS and MAL of only 1 trading period would have produced exorbitant profits, however, over longer periods these models would have been highly unprofitable).

- As the study shows persistent stock price runs which can profitably be exploited by technical models have occurred over the past 20 years on the basis of 30-minutes-data but not on the basis of daily data as in the 1960s and 1970s (over the late 1990s technical models based on higher data frequencies like 10 or 5 minutes might have been even more profitable than 30-minute-models due to the increased "speed" of transactions. This development makes it difficult to successfully use technical systems for those private traders ("dentists and doctors") who practice trading only in the evening.

- The high "speed" of stock (futures) trading place even those amateurs who have become "day traders" at a disadvantage compared to professional traders since the latter can have their trades executed quicker and usually at smaller transaction costs than the former.

There are at least three reasons for why technical trading has become increasingly popular among professionals as well as amateur traders. First, computer software for testing and using technical models as well as the internet (providing access to price data in "real time" as well as quick execution of trading orders) have strongly facilitated the use of technical trading systems. This development has contributed to the increase in the "speed" of transactions in financial markets. Second, the high "speed" of transactions and price changes has made it progressively more difficult to base expectations and transactions on fundamental "news" which occur much less frequently than price changes. Third, technical trading software enables one to find among an almost infinite number of technical models – combining types of models, the size of their parameters and the data frequencies used – those which would have produced high profits. The promising results of this "model mining" seduce more and more agents – in particular amateurs – to follow the respective trading strategies.

9.3 Technical analysis and market efficiency

The efficient market hypothesis holds that utility maximizing agents form their expectations rationally, e.g., according to the true (capital asset pricing) model. Therefore financial prices follow a path determined by the fundamental equilibrium conditions. Stock prices, for example, are determined by the transactions of rational market agents in such a way that they equalize the discounted and risk-adjusted stream of future earnings. Since prices fully reflect all available information at any point in time, trading strategies which use only the information contained in past prices cannot be consistently profitable (Fama, 1970; for a more recent paper on the efficient market hypothesis see Fama, 1998).

The concept of technical analysis and its use in practice are in sharp contrast to the efficient market hypothesis. Technical models disregard market fundamentals. Instead they use only the information contained in past prices in order to identify the direction of persistent price trends (technical trading does not imply any kind of quantitative price expectations). The results of this study show that technical stock futures trading was consistently profitable in both markets, the S&P 500 as well as the DAX market. Since aggregate transactions and positions of technical models exert an excess demand (supply) on the market, use of these models was destabilizing and profitable at the same time (in contrast to the classical argument of Friedman, 1953).

9.4 Technical analysis and the noise trader approach

The noise trader approach to finance considers the existence of those market agents who base their expectations and transactions not on fundamental news but on any other kind of information or even just on individual sentiments or market "moods", summarized under the term "noise" (Black, 1986). Hence, noise traders comprise very different types of market participants like people who adhere to market "gurus", people who follow the general "mood" of the market ("bullishness" or "bearishness") and also traders who base their transactions on technical analysis. However, the noise trader approach does not differentiate between these heterogeneous groups of market agents.[25])

The main conclusions of the noise-trader approach can be summarized as follows (Cutler-Poterba-Summers, 1991; De Long-Shleifer-Summers-Waldmann, 1990A and 1990B). First, being non-rational, the behavior of noise traders is largely unpredictable. Second, since trading strategies of noise traders are often correlated (e.g., through a common perception of the "mood" in the market place) they produce aggregate demand (supply) shifts. Third, the unpredictable behavior of noise traders together with their price effects increase price volatility and, hence, the risk of trading. Fourth, the higher risk prevents rational traders from sufficiently arbitraging between the market price of an asset and its fundamental value. Fifth, if noise traders engage in positive feedback strategies it might be profitable for rational traders to get on the bandwagon themselves. Sixth, any positive return noise traders might earn only compensates them for bearing higher risk. Seventh,

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[25]) The causes of the differences between the actual behavior of market agents and the purely rational behavior of utility maximizing agents assumed in standard equilibrium theory are analyzed in detail in the growing literature under the heading "behavioral finance". For recent surveys see Camerer, 1997; Conlisk, 1996; De Bondt and Thaler, 1996; Shiller, 1999.

except for the compensating returns for bearing risk, noise trading cannot be profitable in the long run since it is based on useless information.

The main results of this study do not support most of these conclusions as regards the most popular type of noise trading, e. g., technical trading. First, the high returns of technical trading in sample and out of sample together with the low probability of making an overall loss when strictly following the same trading rule conflicts with the conclusion of the noise trader approach that feedback trading will not produce returns in excess of the risk incurred by this type of noise trading. Second, the profitability of technical trading stems from the systematic exploitation of persistent price trends and can therefore hardly be interpreted as the market's reward for bearing risk. Third, the aggregate trading behavior of technical models is much less unpredictable than assumed by the noise trader approach. This becomes particularly clear if one looks at the systematic pattern in the movements of the aggregate position index.

9.5 Technical analysis and expectations formation

By following technical models traders (implicitly) form price expectations only in a qualitative manner, e. g., about the direction of price changes. However, technical trading does not even imply that the single trading signals correctly forecast the direction of subsequent price movements in most cases. By contrast, technical traders know from experience that trading signals are more often wrong than they are right (i.e., the number of unprofitable trades exceeds the number of profitable trades). The only "forecast" implied by the use of technical models concerns the asset price dynamics as a whole. It is assumed that persistent price trends occur sufficiently often as to compensate technical traders for the more frequent losses caused by short-term price fluctuations.

Whether technical trading is irrational or rational in the sense that it enables one to earn extra profits can only be judged on empirical grounds. If asset prices actually move in a sequence of upward and downward trends which can be profitably exploited by technical trading systems, then following these feedback strategies should not be considered irrational even though they certainly are non-fundamentalist. The phenomenon that price changes often develop into persistent trends is explained by the interaction between technical and non-technical traders. However, this study shows that price trends continue for some time after technical models have already taken the "right" position in the market.

Hence, at least the last phase of price trends (which is essential for technical trading to be profitable) is brought about by the transactions of non-technical noise traders. This means, however, that technical traders follow the same strategy as those rational traders in the noise trader approach who imitate the behavior of noise traders and exploit this behavior at the same time (DeLong-Shleifer-Summers-Waldmann, 1990B).

9.6 Technical analysis and the system of asset price determination

On the one hand, technical trading systems profitably exploit the persistence of price movements in asset markets, on the other hand, the use of these trading systems strengthen and lengthen price trends since buy (sell) signals as well as long (short) positions of technical models are clustered over time. This interaction between technical trading and asset price dynamics might have contributed to a gradual change in the system of asset price determination as a whole in a way that can be hypothesized as follows.

The profitability of technical trading causes more and more agents to base their activity on this strategy. As a consequence, the persistence of price trends rises, feeding back upon the profitability of technical models. The related increase in the volume of transactions is fostered by the diffusion of new information and communication technologies. They enable traders to apply technical models on data frequencies higher than daily data (e.g., hourly, minute or even tick-by-tick data) which in turn increases the speed of transactions. Under these conditions it becomes progressively more difficult to form expectations about the fundamental price equilibrium and it becomes more risky to bet on a reversal of the current price to this level (as stressed by the noise trader approach). The more asset prices deviate from fundamental values the more unprofitable fundamentalist trading becomes. As such, destabilizing speculation is not wiped out of the market as in Friedman's case but rather stabilizing speculation is squeezed out. At the end of such a process all agents perceive price dynamics primarily as a sequence of trends interrupted by sideways fluctuations.

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 rational adaptation to inherently unstable and progressively irrational markets.

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Figure 1b: Technical trading signals for DAX 500 futures contract 2000
Daily data

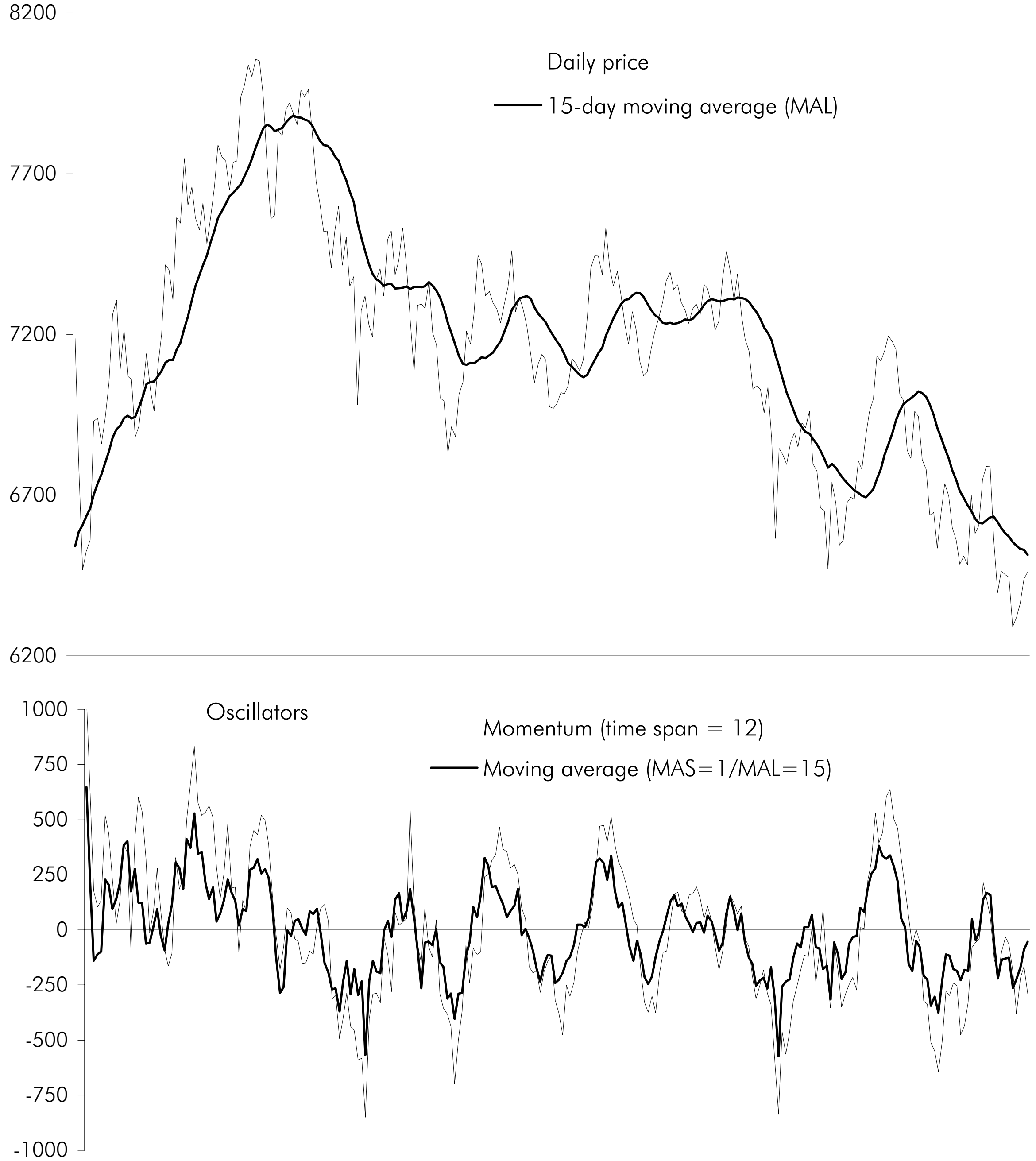

Figure 2b: Technical trading signals for DAX futures contract
July and August 2000, 30-minutes-data

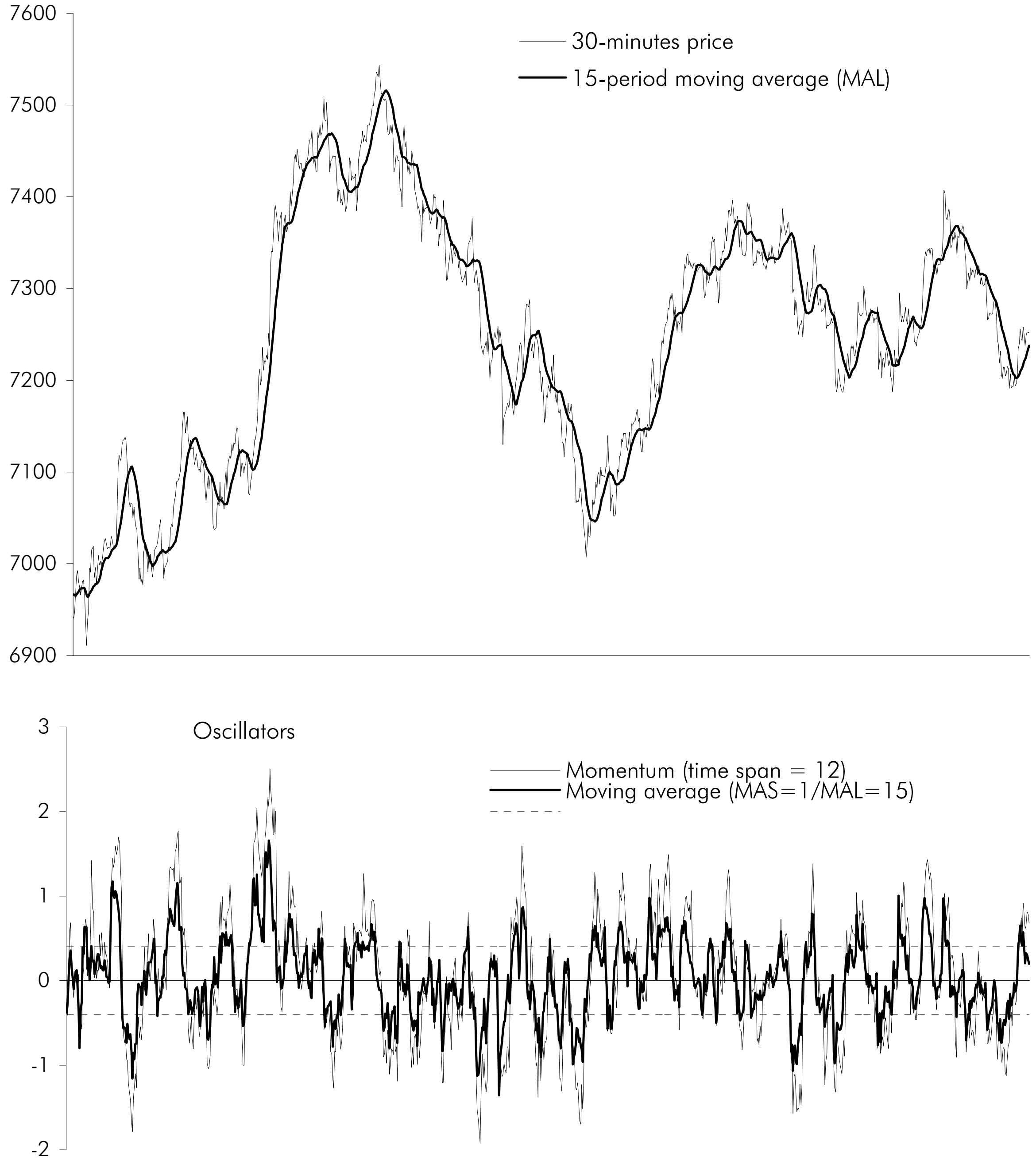

Figure 3b: Technical trading signals for DAX futures contract
July and August 2000, 30-minutes-data

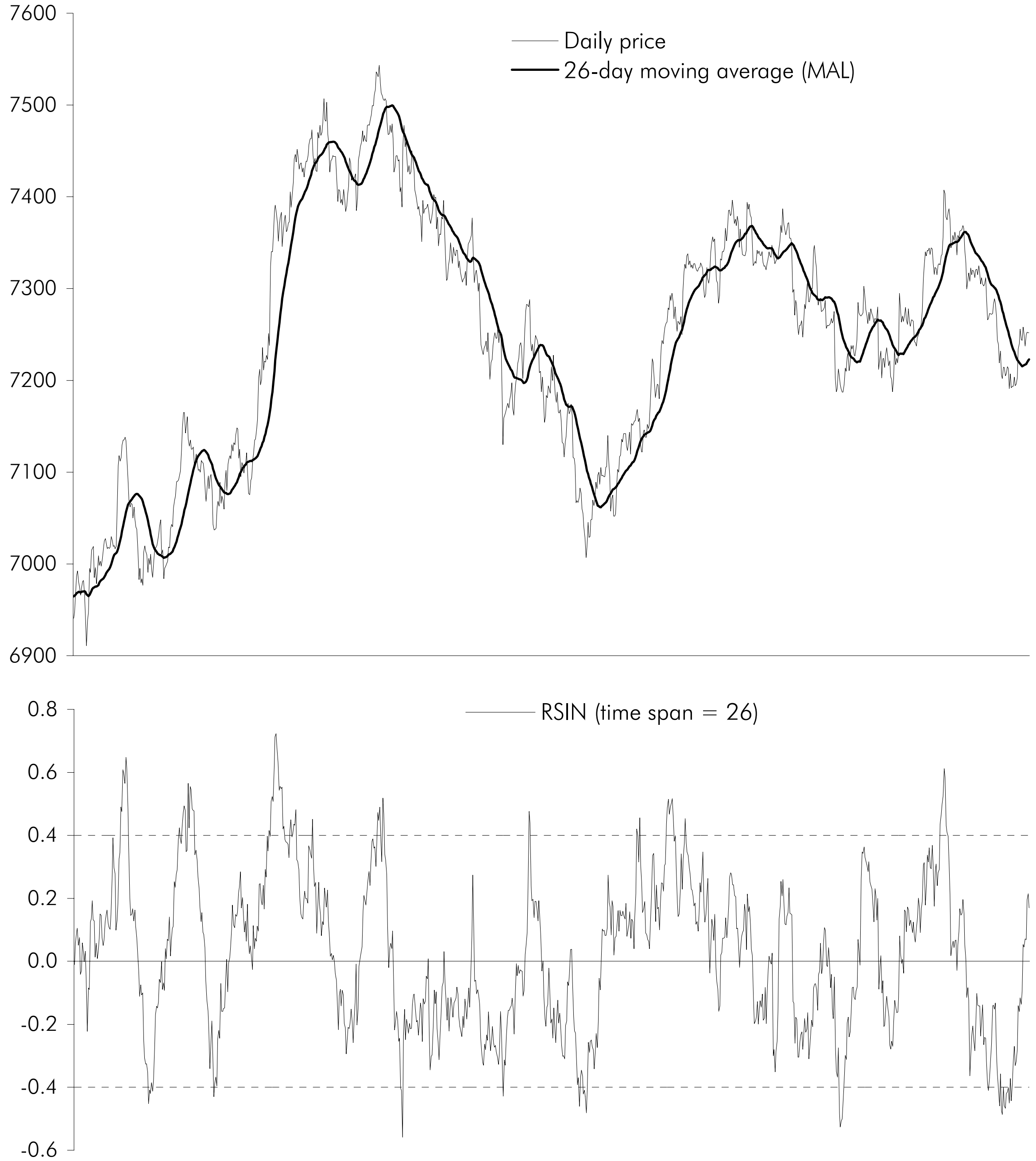

Figure 4b: Distribution of 2580 trading systems by the gross rate of return 1960-2000
DAX 500 spot market, daily data

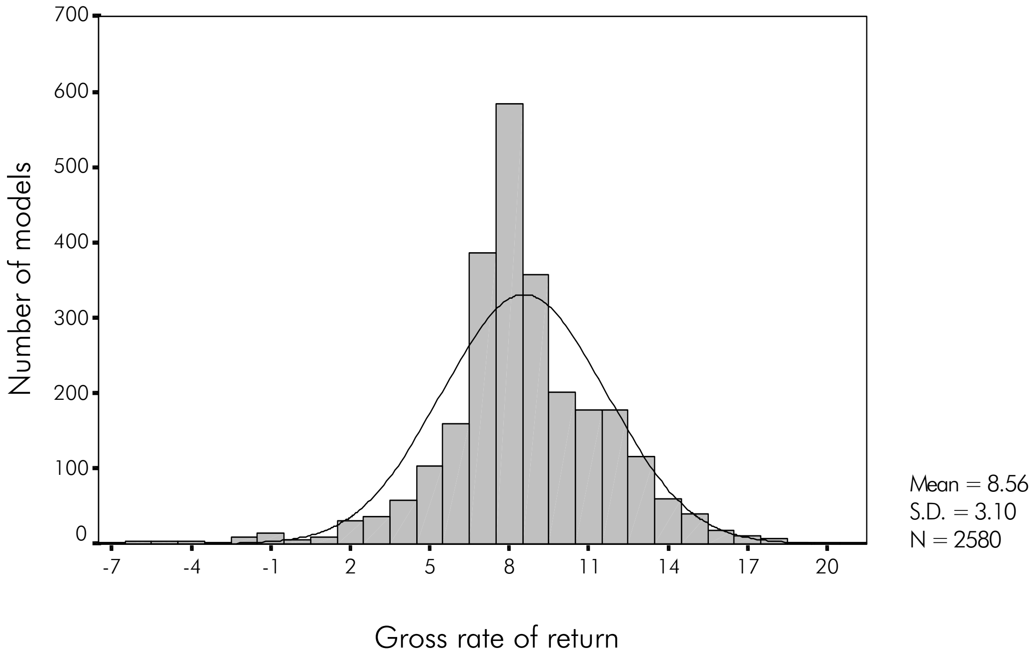

Figure 5b: Profitability and riskiness of 2580 technical trading systems 1960-2000
DAX 500 spot market, daily data

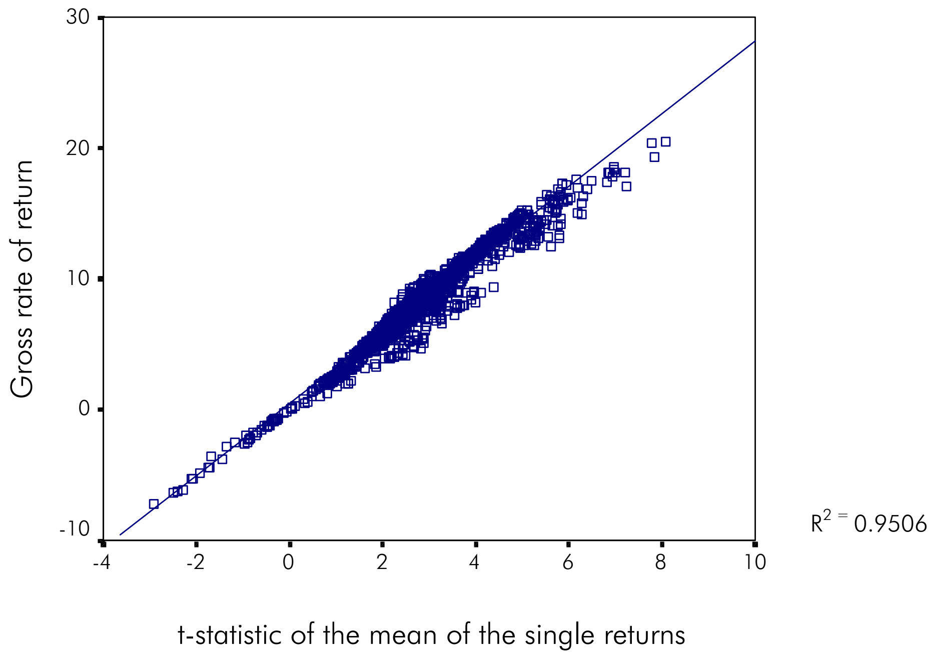

Figure 6b: Distribution of 2580 trading systems by the ratio between the number of profitable and unprofitable positions 1960-2000
DAX 500 spot market, daily data

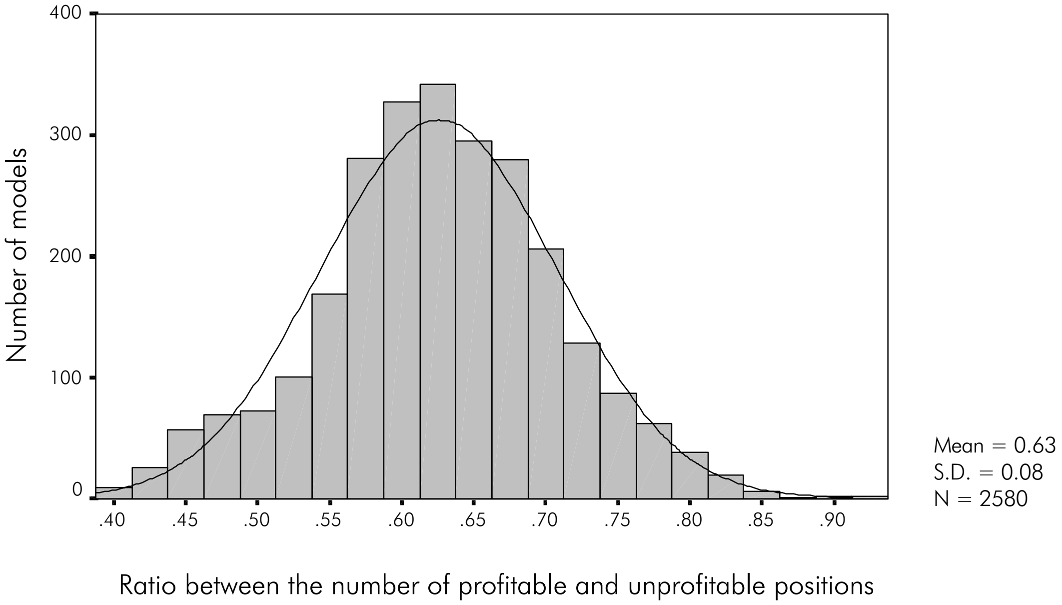

Figure 7b: Distribution of 2580 trading systems by the ratio between the daily return during profitable and unprofitable positions 1960-2000
DAX 500 spot market, daily data

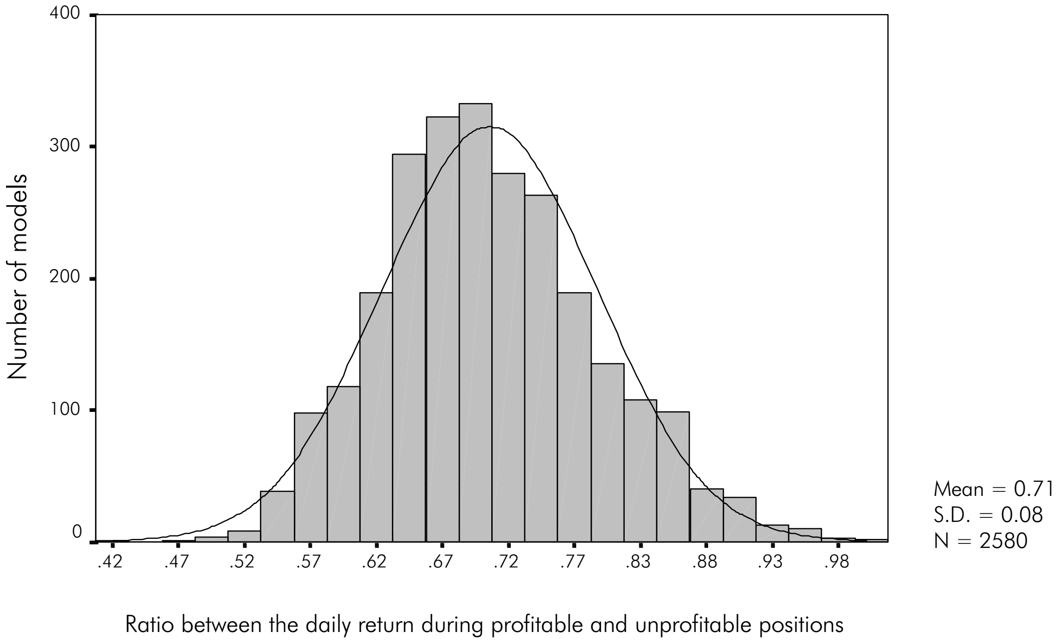

Figure 8b: Distribution of 2580 trading systems by the ratio between the duration of profitable and unprofitable positions 1960-2000
DAX 500 spot market, daily data

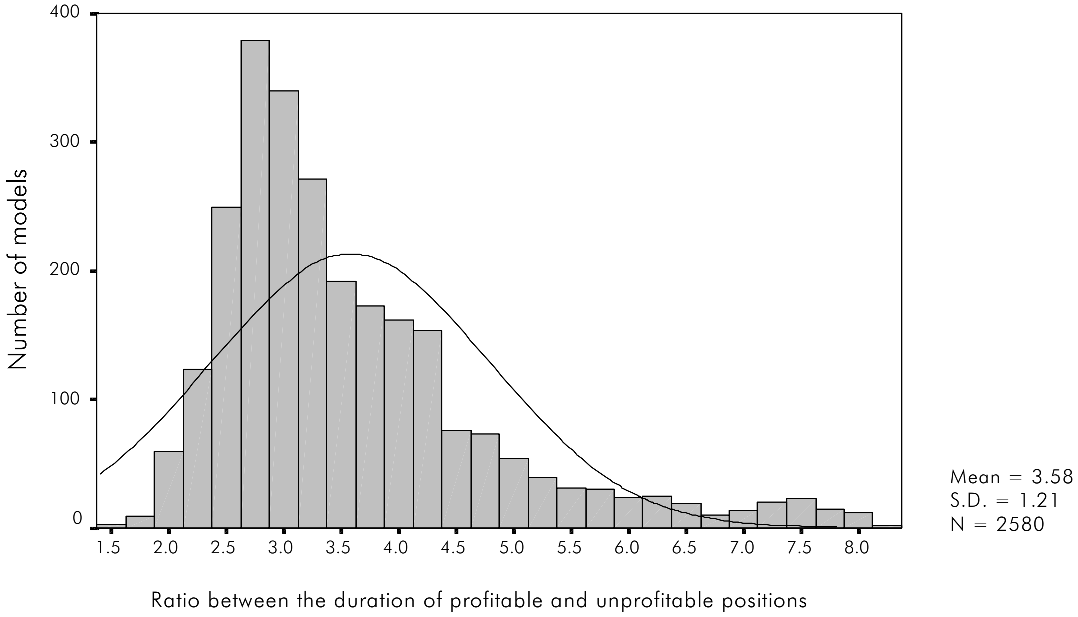

Figure 9b: Distribution of 2580 trading systems by the gross rate of return 1992-2000
DAX 500 futures market, daily data

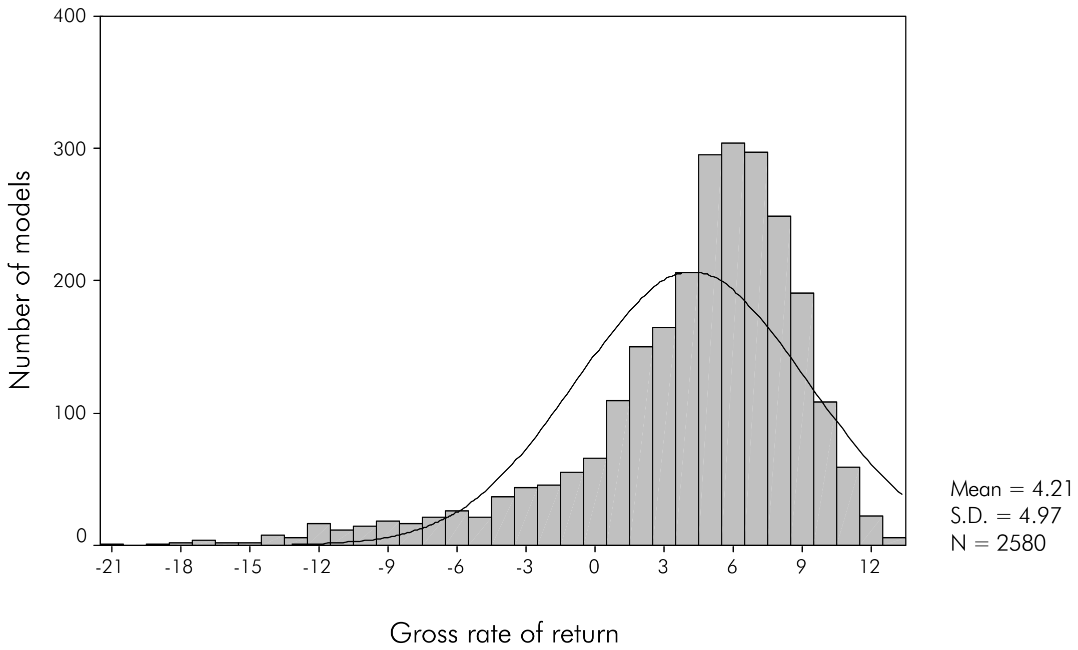

Figure 10b: Profitability and riskiness of 2580 technical trading systems 1992-2000
DAX 500 futures market, daily data

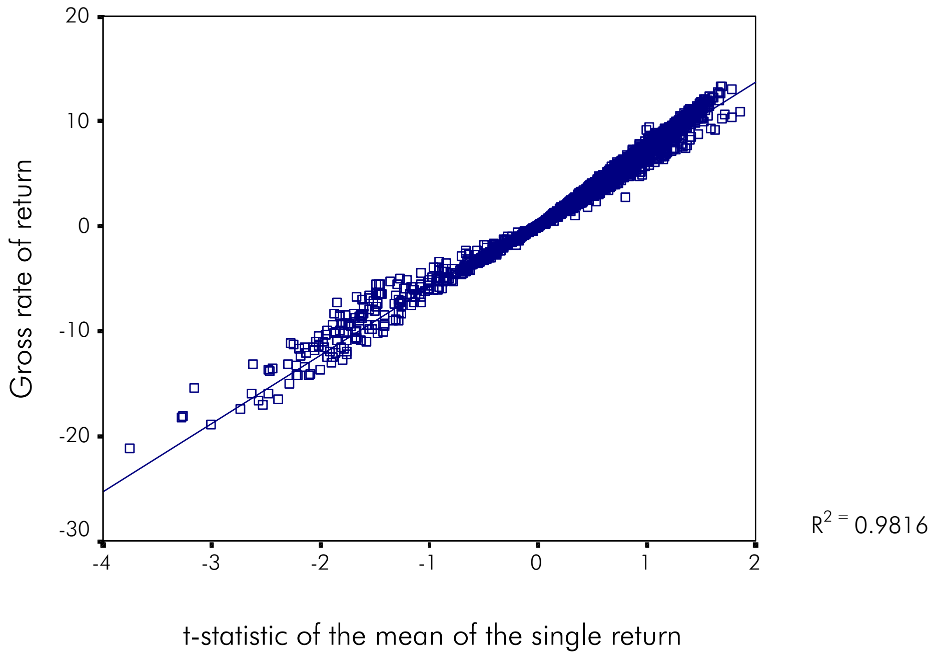

Figure 11b: Distribution of 2580 trading systems by the ratio between the number of profitable and unprofitable positions 1992-2000
DAX 500 futures market, daily data

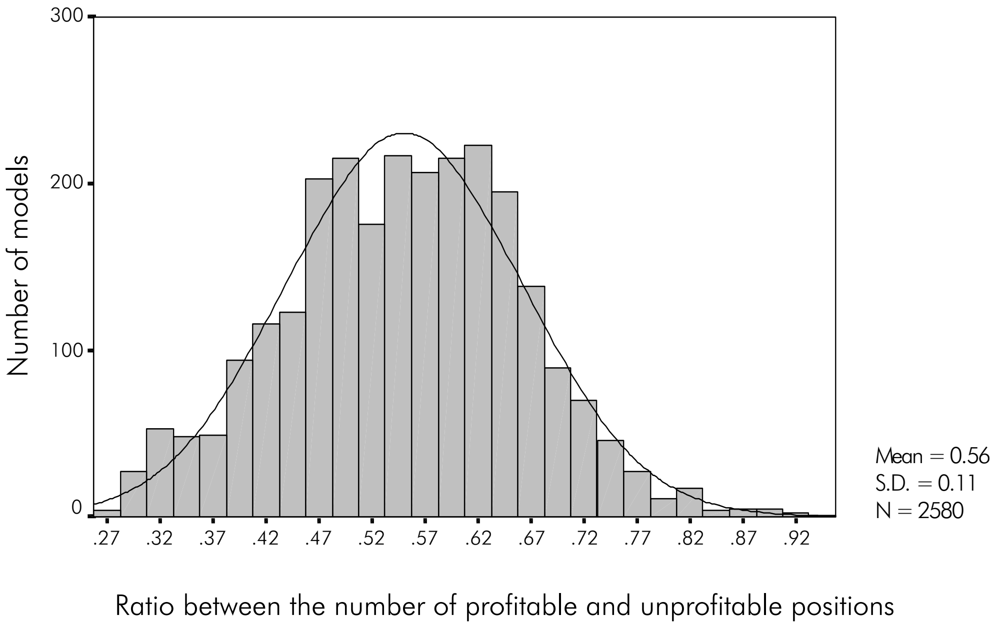

Figure 12b: Distribution of 2580 trading systems by the ratio between the daily return during profitable and unprofitable positions 1992-2000
DAX 500 futures market, daily data

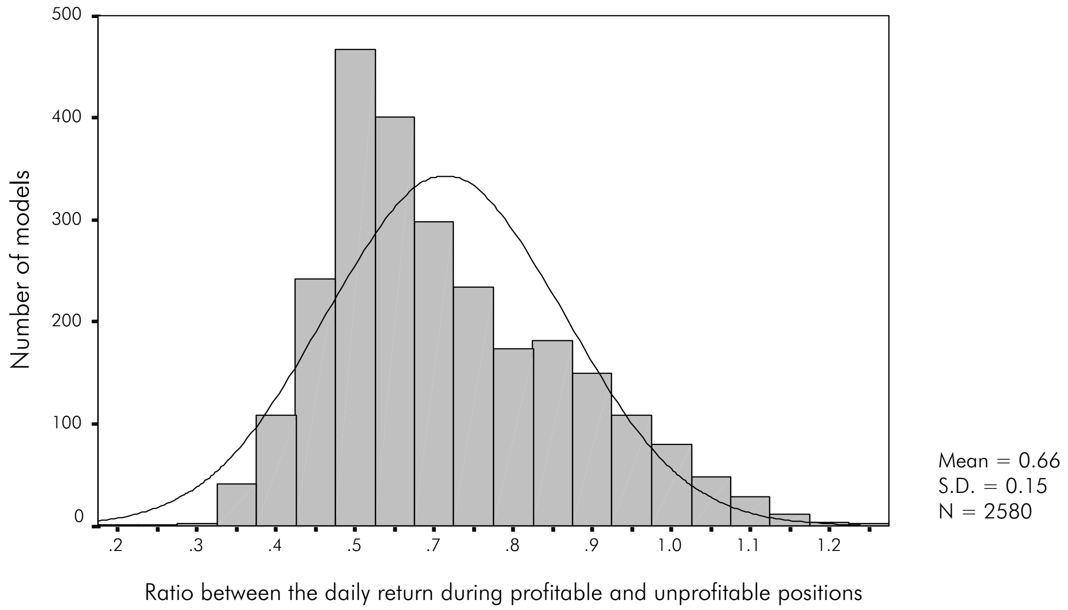

Figure 13b: Distribution of 2580 trading systems by the ratio between the duration of profitable and unprofitable positions 1992-2000
DAX 500 futures market, daily data

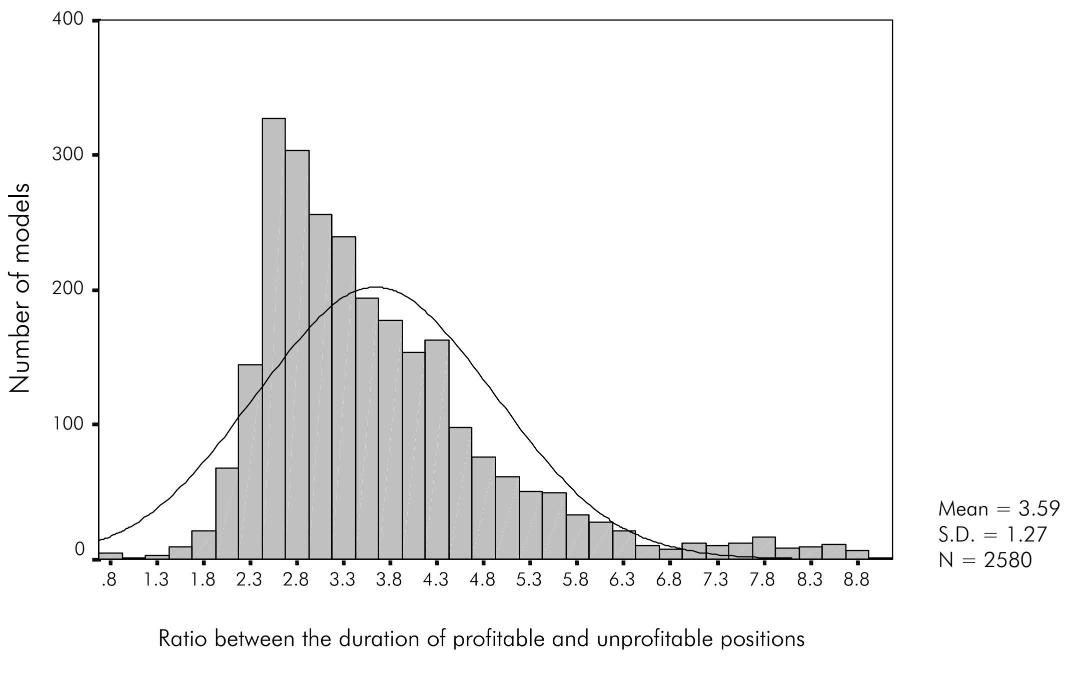

Figure 14b: Distribution of 2580 trading systems by the gross rate of return 1997-2000
DAX 500 futures market, 30 minutes data

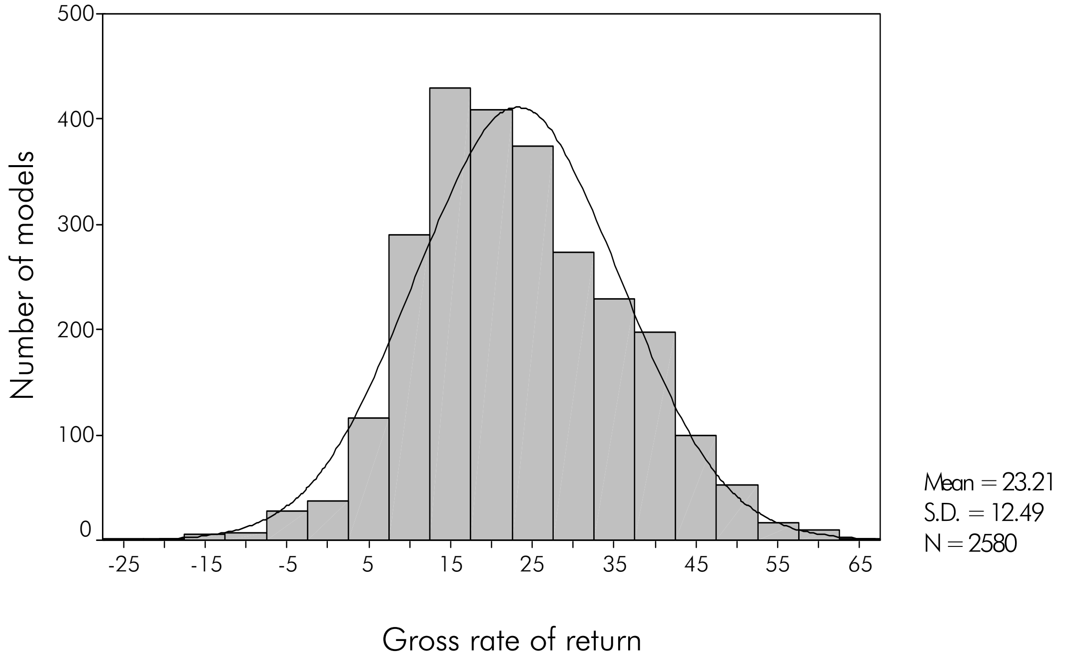

Figure 15b: Distribution of 2580 trading systems by the net rate of return 1997-2000
DAX 500 futures market, 30 minutes data

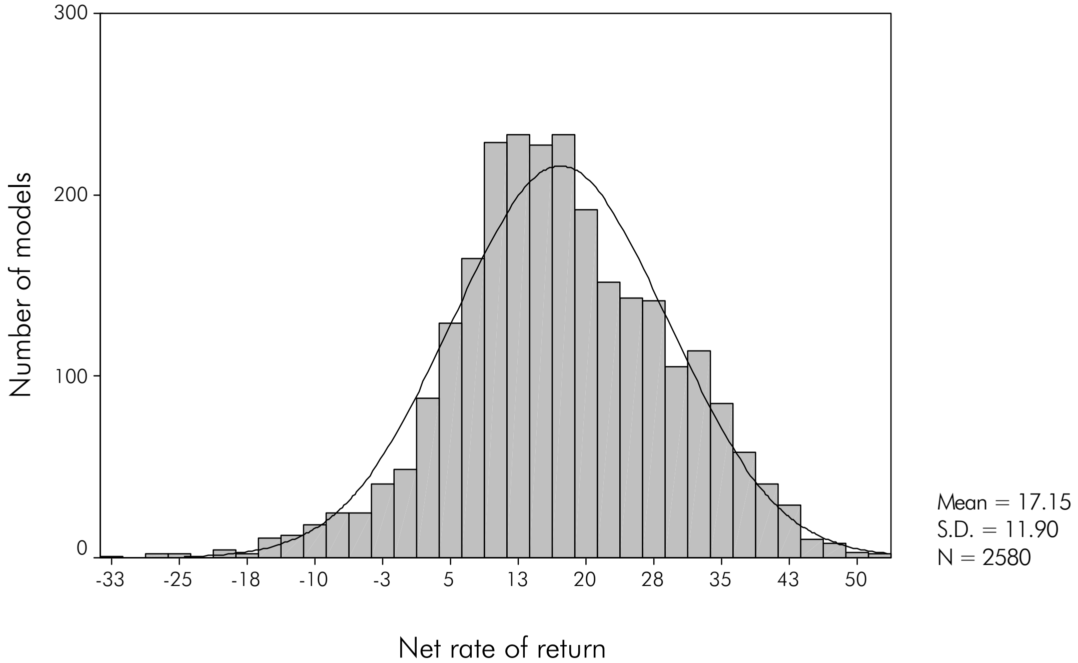

Figure 16b: Profitability and riskiness of 2580 technical trading systems 1997-2000
DAX 500 futures market, 30 minutes data

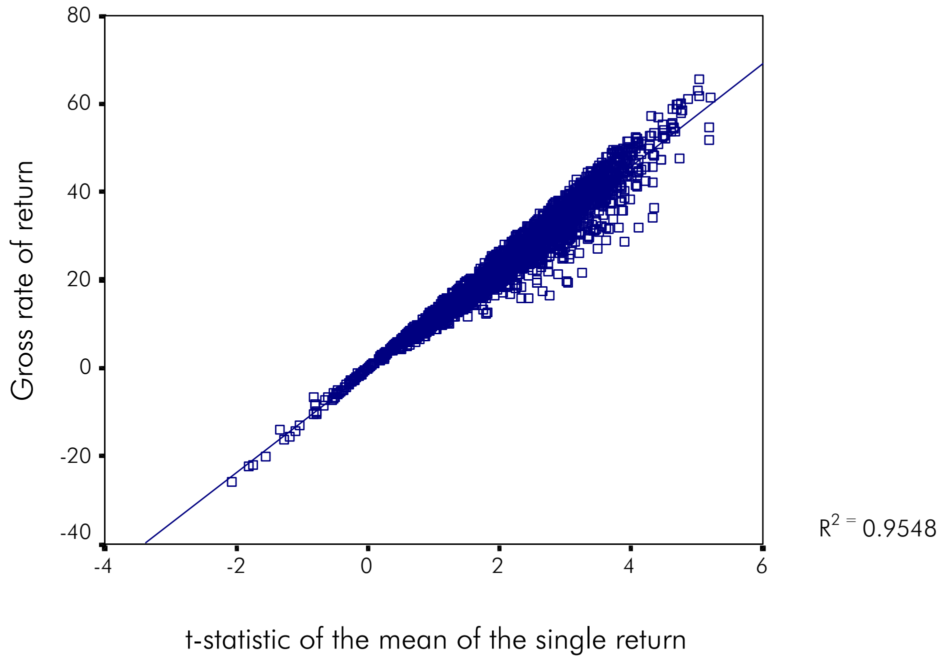

Figure 17b: Distribution of 2580 trading systems by the ratio between the number of profitable and unprofitable postitions 1997-2000
DAX 500 futures market, 30 minutes data

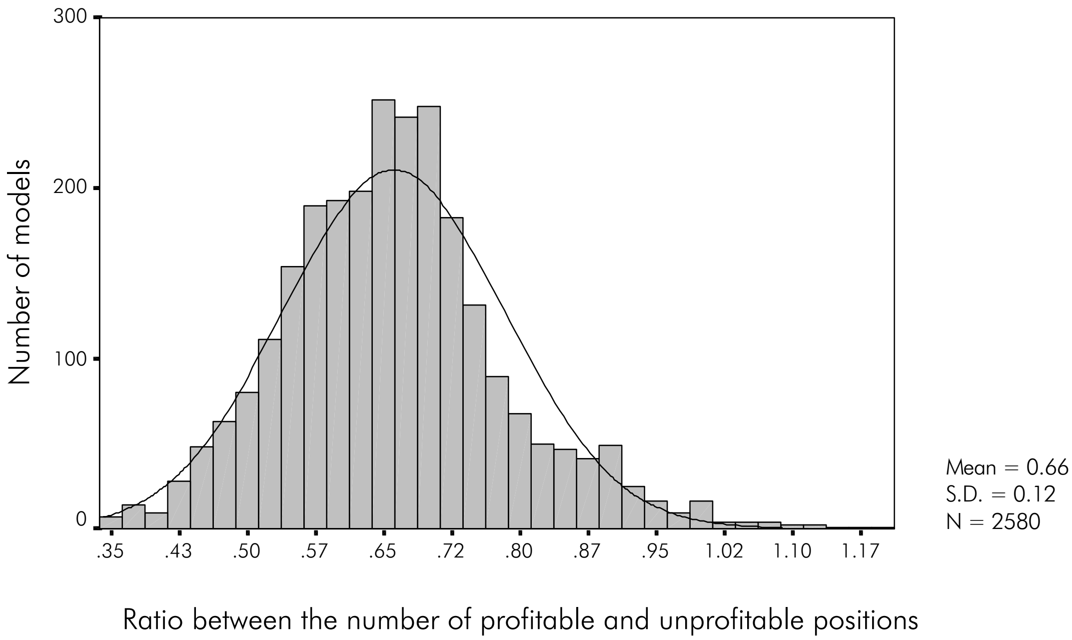

Figure 18b: Distribution of 2580 trading systems by the ratio between the daily return during profitable and unprofitable positions 1997-2000

DAX 500 futures market, 30 minutes data

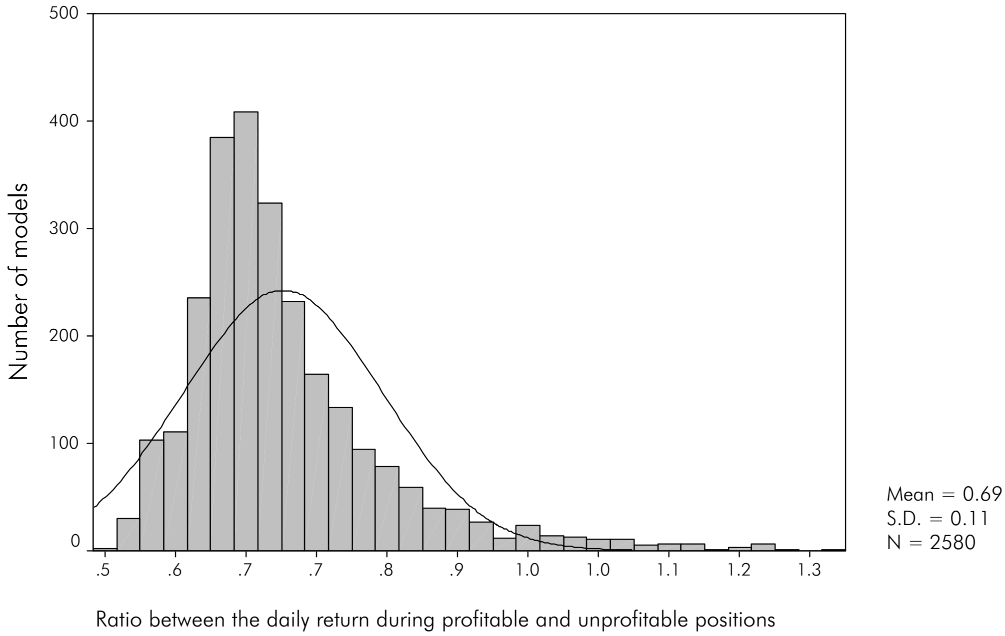

Figure 19b: Distribution of 2580 trading systems by the ratio between the duration of profitable and unprofitable positions 1997-2000
DAX 500 futures market, 30 minutes data

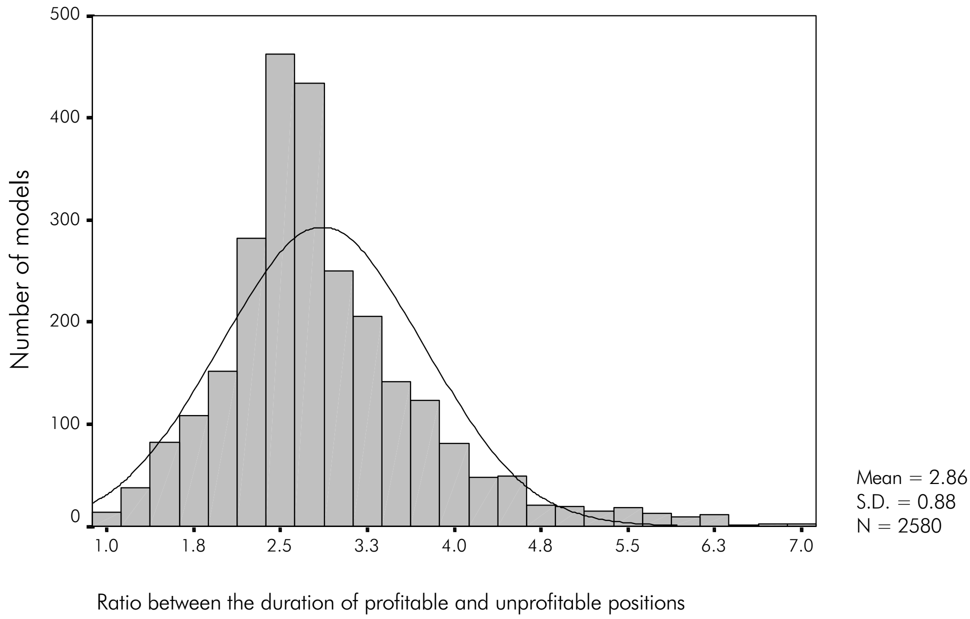

Figure 20b: Duration of profitable positions and the parameters of trading systems (moving average models (SG1))
DAX 500 futures market, 30 minutes data

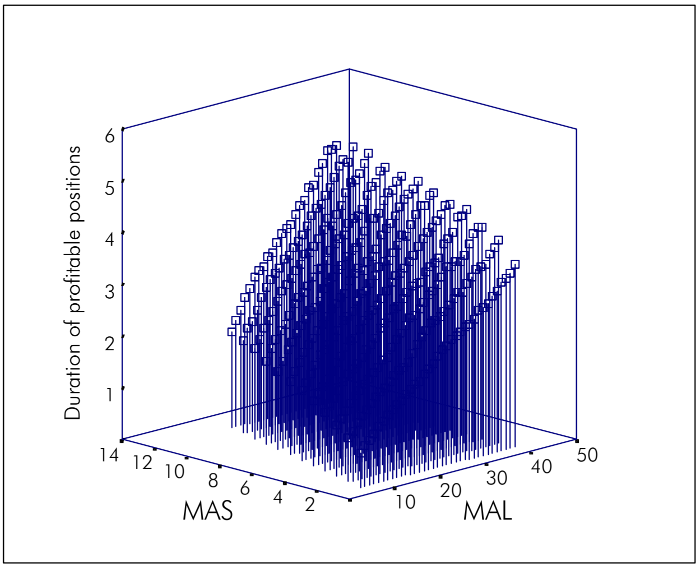

Figure 21b: Duration of profitable positions and the parameters of trading systems (momentum models (SG1))
DAX 500 futures market, 30 minutes data

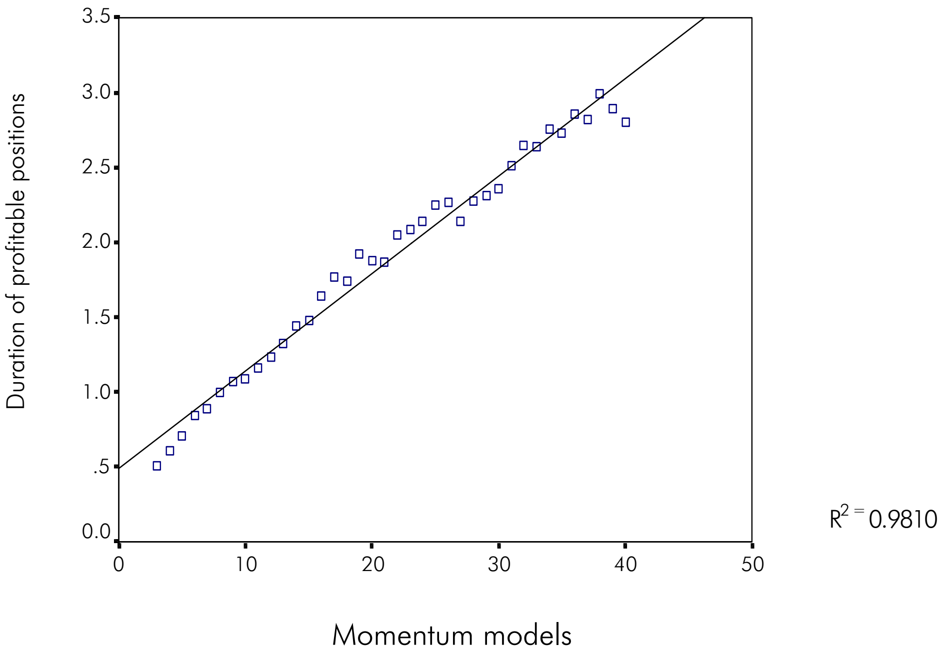

Figure 22b: Aggregate trading signals and stock price dynamics
July and August 2000, 30-minutes-data

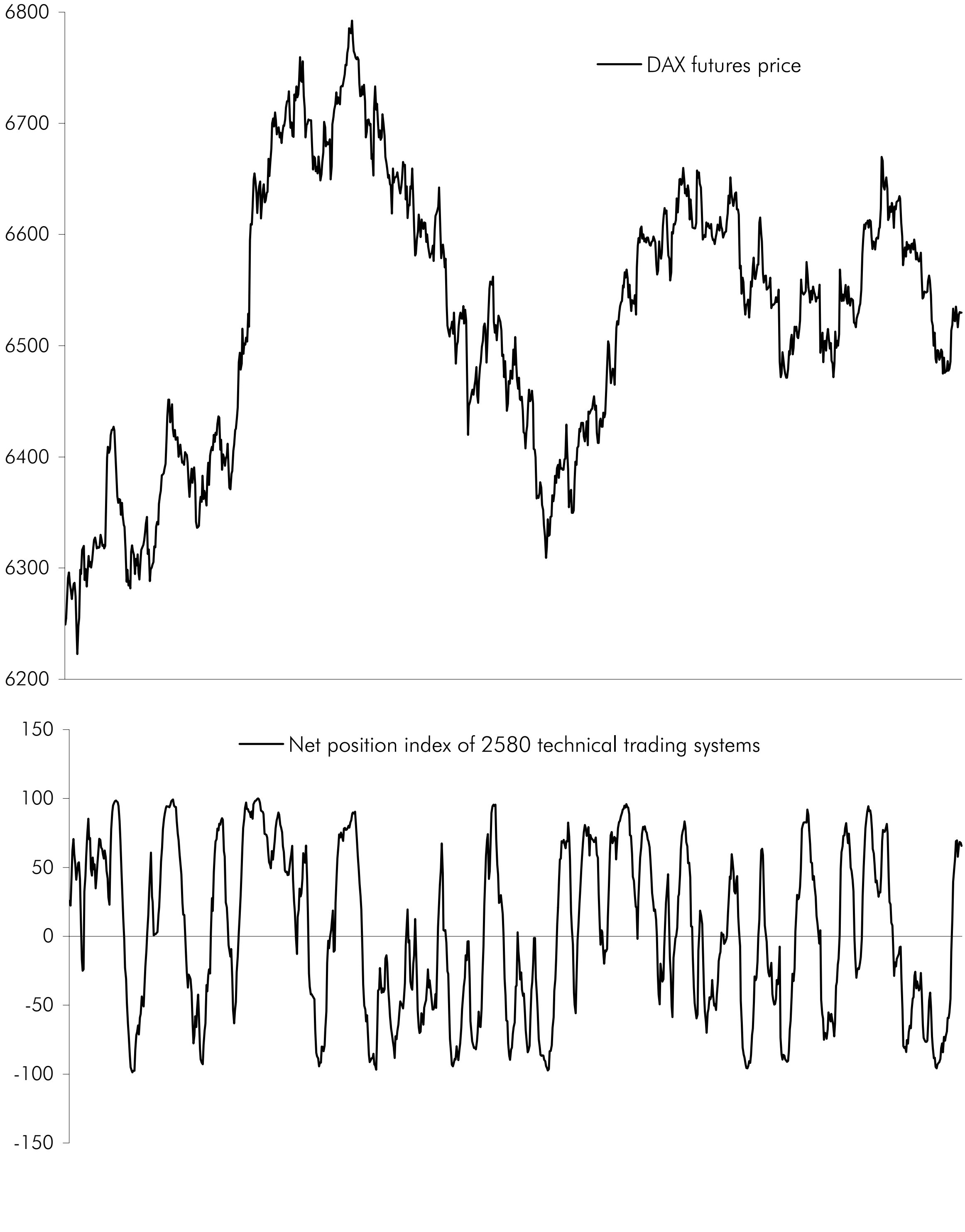

Figure 23b: Aggregate trading signals of momentum and contrarian models and stock price dynamics
July and August 2000, 30-minutes-data

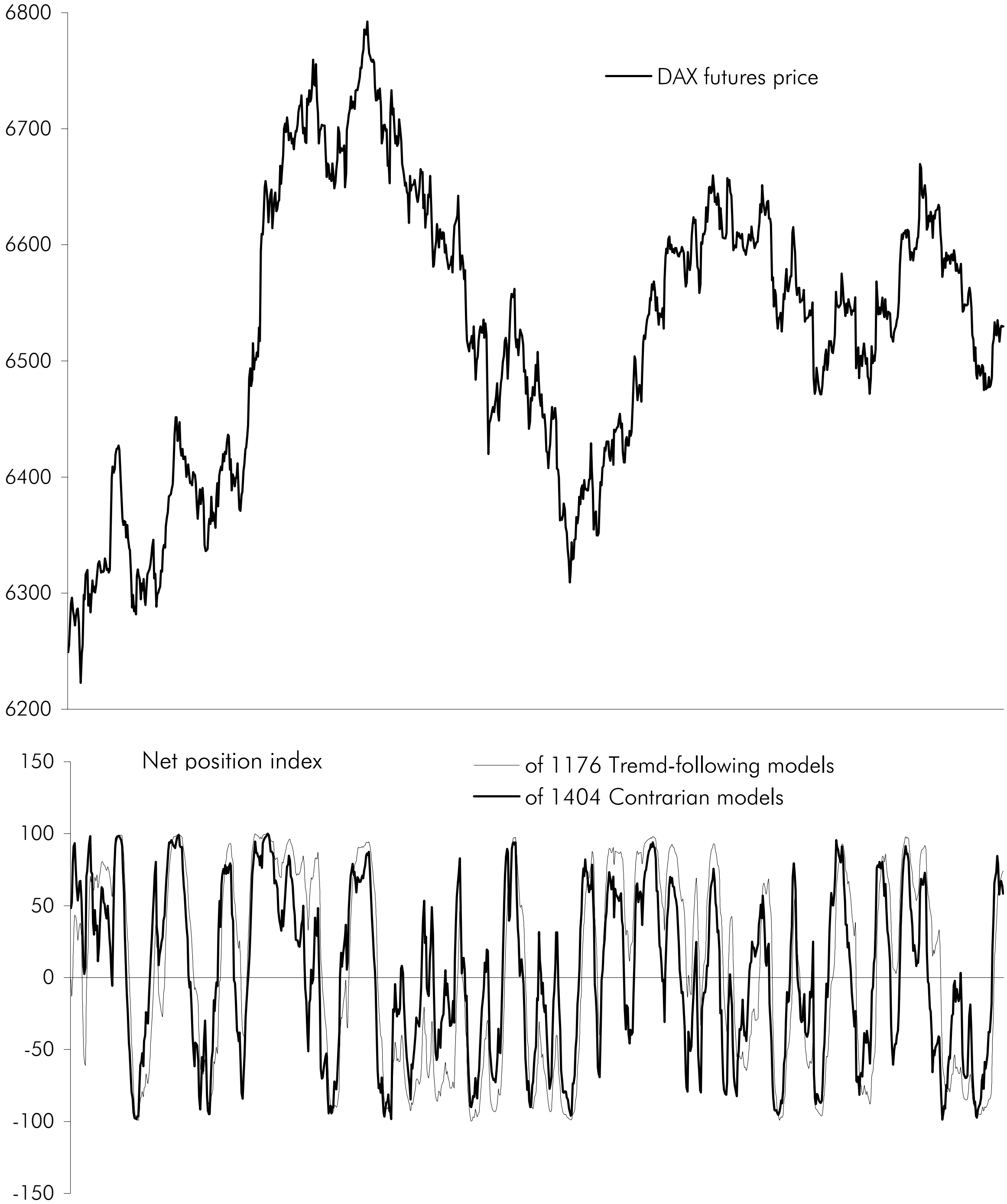

Table 1b: Performance of technical trading systems

Price series: Daily prices of the DAX futures contract
Begin of trading: 01/01/2000
End of trading: 12/29/2000
Signal generating process
Trading systems: Moving average (SG1)
Short-term moving average (MAS): 1
Long-term moving average (MAL): 15

The sequence of long, short and neutral positions

Date	Signal	Duration	Price	Single rate of return	Rate of return per year
01/03/2000	l	0	7,188	0.0	0.0
01/05/2000	s	2	6,467	–10.0	– 1,830.6
01/10/2000	l	5	6,930	– 7.2	– 896.3
01/25/2000	s	15	6,881	– 0.7	– 296.9
01/27/2000	l	2	7,024	– 2.1	– 303.8
01/31/2000	s	4	7,029	0.1	– 259.5
02/02/2000	l	2	7,099	– 1.0	– 254.3
03/14/2000	s	41	7,730	8.9	– 61.8
03/22/2000	l	8	7,921	– 1.9	– 64.0
.	.	.	.	.	.
.	.	.	.	.	.
09/11/2000	s	3	7,259	– 1.8	– 41.6
10/05/2000	l	24	6,909	6.0	– 30.1
10/09/2000	s	4	6,797	– 1.6	– 31.8
10/25/2000	l	16	6,807	– 0.1	– 30.2
11/13/2000	s	19	6,840	0.5	– 27.9
12/06/2000	l	23	6,700	2.0	– 23.8
12/07/2000	s	1	6,581	– 1.8	– 25.6
12/11/2000	l	4	6,749	– 2.6	– 28.0
12/14/2000	s	3	6,565	– 2.7	– 30.6
12/29/2000	n	15	6,460	2.7	– 26.6

The profitability of the trading system

Gross rate of return	–26.6
Net rate of return	–27.5
Number of positions	
Long	20.2
Short	20.2
Neutral	0
Average duration of positions	9.0
Long	8.0
Short	10.0
Neutral	0
Sum of profits	29.5
Profitable positions	
Number (NPP)	9.1
Average return	
Per position (RPP)	3.2
Per day (DRP)	0.15
Average duration (DPP)	21.4
Sum of losses	–56.1
Unprofitable positions	
Number (NPL)	31.3
Average return	
Per position (RPL)	–1.8
Per day (DRL)	–0.33
Average duration (DPL)	5.4

Table 2b: Performance of technical trading systems

Price series: Daily prices of the DAX futures contract
Begin of trading: 01/01/2000
End of trading: 12/29/2000
Signal generating process
Trading systems: Momentum (SG1)
Time span i of M: 12

The sequence of long, short and neutral positions

Date	Signal	Duration	Price	Single rate of return	Rate of return per year
01/03/2000	l	0	7,188	0.0	0.0
01/19/2000	s	16	7,090	–1.4	– 31.1
01/20/2000	l	1	7,216	–1.8	– 67.4
01/26/2000	s	6	6,916	–4.2	–115.8
01/27/2000	l	1	7,024	–1.6	–134.7
02/01/2000	s	5	6,961	–0.9	–122.8
02/04/2000	l	3	7,418	–6.6	–186.1
02/29/2000	s	25	7,650	3.1	– 84.4
03/01/2000	l	1	7,736	–1.1	– 90.0
.	.	.	.	.	.
.	.	.	.	.	.
10/09/2000	s	3	6,797	–2.3	– 36.7
10/11/2000	l	2	6,660	2.0	– 33.8
10/12/2000	s	1	6,650	–0.2	– 33.9
10/25/2000	l	13	6,807	–2.4	– 35.3
11/14/2000	s	20	6,814	0.1	– 33.0
11/15/2000	l	1	6,961	–2.2	– 35.3
11/16/2000	s	1	6,945	–0.2	– 35.5
12/11/2000	l	25	6,749	2.8	– 29.9
12/14/2000	s	3	6,565	–2.7	– 32.5
12/29/2000	n	15	6,460	2.7	– 28.4

The profitability of the trading system

Gross rate of return	–28.4
Net rate of return	–29.3
Number of positions	
Long	19.2
Short	19.2
Neutral	0
Average duration of positions	9.5
Long	9.1
Short	9.9
Neutral	0
Sum of profits	23.4
Profitable positions	
Number (NPP)	12.1
Average return	
Per position (RPP)	1.9
Per day (DRP)	0.12
Average duration (DPP)	16.6
Sum of losses	–51.8
Unprofitable positions	
Number (NPL)	26.3
Average return	
Per position (RPL)	–2.0
Per day (DRL)	–0.32
Average duration (DPL)	6.2

Table 3b: Performance of technical trading systems

Price series: 30-minutes prices of the DAX futures contract
Begin of trading: 01/01/2000
End of trading: 12/29/2000
Signal generating process
Trading systems: Moving average (SG1)
Short-term moving average (MAS): 1
Long-term moving average (MAL): 15

The sequence of long, short and neutral positions

Date	Signal	Duration	Price	Single rate of return	Rate of return per year
09:13:49/01/03/2000	l	0	7,188.0	0.0	0.0
13:30:00/01/03/2000	s	0.18	7,056.0	– 1.8	– 3,767.7
16:30:00/01/04/2000	l	1.12	6,659.0	5.6	1,061.8
09:09:25/01/05/2000	s	0.69	6,467.0	– 2.9	165.7
12:30:00/01/05/2000	l	0.14	6,601.0	– 2.1	– 199.1
14:30:01/01/05/2000	s	0.08	6,536.0	– 1.0	– 353.6
16:30:07/01/05/2000	l	0.08	6,571.5	– 0.5	– 426.8
17:00:02/01/05/2000	s	0.02	6,538.0	– 0.5	– 503.1
09:30:00/01/06/2000	l	0.69	6,563.5	– 0.4	– 435.5
10:00:04/01/06/2000	s	0.02	6,517.0	– 0.7	– 517.8
.	.	.	.	.	.
.	.	.	.	.	.
10:00:04/07/07/2000	s	0.71	7,011.0	0.1	57.8
10:30:00/07/07/2000	l	0.02	7,015.5	– 0.1	57.6
11:00:00/07/07/2000	s	0.02	6,984.0	– 0.5	56.7
13:30:01/07/07/2000	l	0.1	7,018.5	– 0.5	55.7
14:00:00/07/10/2000	s	3.02	7,125.0	1.5	57.8
13:00:04/07/11/2000	l	0.96	7,097.5	0.4	58.2
13:30:01/07/11/2000	s	0.02	7,080.0	– 0.3	57.7
17:30:04/07/11/2000	l	0.17	7,089.0	– 0.1	57.4
18:00:15/07/11/2000	s	0.02	7,066.0	– 0.3	56.8
.	.	.	.	.	.
.	.	.	.	.	.
19:00:02/12/21/2000	l	0.02	6,268.5	– 0.1	51.3
13:00:39/12/22/2000	s	0.75	6,292.0	0.4	51.6
15:00:01/12/22/2000	l	0.08	6,305.5	– 0.2	51.3
15:30:00/12/27/2000	s	5.02	6,364.0	0.9	51.6
17:30:04/12/27/2000	l	0.08	6,391.0	– 0.4	51.1
19:31:27/12/27/2000	s	0.08	6,378.0	– 0.2	50.9
09:08:00/12/28/2000	l	0.57	6,440.0	– 1.0	49.8
13:30:00/12/28/2000	s	0.18	6,400.0	– 0.6	49.2
16:30:00/12/28/2000	l	0.12	6,430.0	– 0.5	48.7
18:00:09/12/28/2000	s	0.06	6,409.0	– 0.3	48.4
09:03:58/12/29/2000	l	0.63	6,460.0	– 0.8	47.5
13:30:23/12/29/2000	n	0.19	6,507.5	0.7	48.2

The profitability of the trading system

Gross rate of return	48.2
Net rate of return	35.7
Number of positions	
Long	310.3
Short	309.2
Neutral	0
Average duration of positions	0.6
Long	0.6
Short	0.6
Neutral	0
Sum of profits	205.5
Profitable positions	
Number (NPP)	194.0
Average return	
Per position (RPP)	1.1
Per day (DRP)	0.82
Average duration (DPP)	1.3
Sum of losses	– 157.3
Unprofitable positions	
Number (NPL)	425.5
Average return	
Per position (RPL)	– 0.4
Per day (DRL)	– 1.37
Average duration (DPL)	0.3

Table 4b: Performance of technical trading systems

Price series: 30-minutes prices of the DAX futures contract
Begin of trading: 01/01/2000
End of trading: 12/29/2000
Signal generating process
Trading systems: Momentum (SG1)
Time span i of M: 12

The sequence of long, short and neutral positions

Date	Signal	Duration	Price	Single rate of return	Rate of return per year
09:13:49/01/03/2000	l	0.00	7,188.0	0.0	0.0
15:00:01/01/03/2000	s	0.24	7,067.0,	−1.7	− 2,555.7
15:00:01/01/05/2000	l	2.00	6,533.5	7.6	955.6
15:59:59/01/05/2000	s	0.04	6,506.5	−0.4	872.1
16:30:07/01/05/2000	l	0.02	6,571.5	−1.0	705.8
09:07:43/01/06/2000	s	0.69	6,524.0	−0.7	454.6
09:30:00/01/06/2000	l	0.02	6,563.5	−0.6	378.8
10:00:04/01/06/2000	s	0.02	6,517.0	−0.7	290.9
17:00:05/01/06/2000	l	0.29	6,534.0	−0.3	236.8
10:00:02/01/11/2000	s	4.71	6,945.0	6.3	383.8
17:00:00/01/11/2000	l	0.29	6,952.0	−0.1	366.0
.	.	.	.	.	.
.	.	.	.	.	.
09:07:03/12/20/2000	s	0.90	6,445.0	−1.3	55.5
19:30:01/12/21/2000	l	1.43	6,274.0	2.7	58.0
15:00:01/12/22/2000	s	0.81	6,305.5	0.5	58.4
17:00:08/12/22/2000	l	0.08	6,323.0	−0.3	58.1
15:30:00/12/27/2000	s	4.94	6,364.0	0.7	57.9
19:00:45/12/27/2000	l	0.15	6,393.0	−0.5	57.4
19:31:27/12/27/2000	s	0.02	6,378.0	−0.2	57.2
09:08:00/12/28/2000	l	0.57	6,440.0	−1.0	56.1
14:00:00/12/28/2000	s	0.20	6,391.0	−0.8	55.3
14:30:15/12/28/2000	l	0.02	6,393.0	−0.0	55.3
15:00:04/12/28/2000	s	0.02	6,399.5	0.1	55.4
16:30:00/12/28/2000	l	0.06	6,430.0	−0.5	54.9
18:00:09/12/28/2000	s	0.06	6,409.0	−0.3	54.5
09:03:58/12/29/2000	l	0.63	6,460.0	−0.8	53.6
14:00:00/12/29/2000	n	0.21	6,500.0	0.6	54.2

The profitability of the trading system

Gross rate of return	54.2
Net rate of return	41.6
Number of positions	
Long	313.3
Short	312.3
Neutral	0
Average duration of positions	0.6
Long	0.6
Short	0.6
Neutral	0
Sum of profits	207.4
Profitable positions	
Number (NPP)	230.4
Average return	
Per position (RPP)	0.9
Per day (DRP)	0.90
Average duration (DPP)	1.0
Sum of losses	−153.2
Unprofitable positions	
Number (NPL)	395.1
Average return	
Per position (RPL)	− 0.4
Per day (DRL)	− 1.14
Average duration (DPL)	0.3

Table 5b: Pattern of technical trading in the DAX futures market, daily data, 1997-2000

	SG1	SG2[1]	SG3[1]	SG4[1]	SG5[1]	SG6[2]
Moving average models (MAS = 1, MAL = 15)						
Gross rate of return	5.0	5.9	5.4	4.1	4.4	4.1
Sum of profits	45.9	44.7	43.8	48.3	44.4	44.9
Profitable positions						
Number	9.3	8.8	10.5	12.0	11.3	11.8
Average return						
Per position	5.0	5.1	4.2	4.0	3.9	3.8
Per day	0.18	0.18	0.19	0.20	0.19	0.19
Average duration in days	27.1	28.2	22.2	20.5	21.0	20.5
Sum of losses	−40.9	−38.7	−38.4	−44.3	−39.9	−40.8
Unprofitable positions						
Number	22.6	20.0	22.3	27.3	24.3	25.1
Average return						
Per position	− 1.8	− 1.9	− 1.7	− 1.6	− 1.6	− 1.6
Per day	−0.36	−0.36	−0.36	−0.38	−0.35	−0.35
Average duration in days	5.1	5.4	4.8	4.3	4.7	4.6
Single rates of return						
Mean	0.16	0.21	0.16	0.10	0.12	0.11
t-statistic	0.44	0.53	0.54	0.39	0.44	0.40
Median	−0.93	−0.95	−0.82	−0.72	−0.76	−0.70
Standard deviation	4.02	4.15	3.50	3.35	3.38	3.36
Skewness	2.04	1.93	1.38	1.40	1.46	1.42
Excess kurtosis	5.73	5.14	2.23	2.47	2.64	2.68
Sample size	127	115	131	157	142	147
Momentum models (Time span = 12)						
1 Gross rate of return	3.4	2.9	− 0.4	− 3.2	0.1	− 3.1
Sum of profits	48.3	47.0	45.3	46.6	46.5	46.5
Profitable positions						
Number	10.5	9.8	11.3	12.3	12.0	12.0
Average return						
Per position	4.6	4.8	4.0	3.8	3.9	3.9
Per day	0.19	0.20	0.19	0.19	0.19	0.19
Average duration in days	23.8	24.4	20.7	19.9	20.4	20.4
Sum of losses	−44.8	−44.1	−45.7	−49.8	−46.4	−49.6
Unprofitable positions						
Number	20.3	18.5	19.5	23.6	21.3	22.6
Average return						
Per position	− 2.2	− 2.4	− 2.3	− 2.1	− 2.2	− 2.2
Per day	−0.39	−0.37	−0.39	−0.41	−0.41	−0.43
Average duration in days	5.6	6.4	6.0	5.1	5.3	5.1
Single rates of return						
Mean	0.11	0.10	−0.01	−0.09	0.00	−0.09
t-statistic	0.25	0.21	−0.03	−0.25	0.01	−0.24
Median	−0.98	−1.05	−0.99	−0.90	−0.90	−0.90
Standard deviation	4.98	5.19	4.57	4.27	4.40	4.36
Skewness	2.75	2.63	2.37	2.55	2.46	2.50
Excess kurtosis	9.25	8.31	7.08	8.56	7.81	8.11
Sample size	123	113	123	143	133	138

Relative strength models (Time span = 12)	SG4[1]	SG5[1]	SG6[2]	SG4[3]	SG5[3]	SG6[4]
Gross rate of return	−23.2	−10.3	−21.9	−16.6	− 7.0	−20.0
Sum of profits	49.9	32.8	40.2	43.3	29.9	35.9
Profitable positions						
Number	15.0	13.0	14.0	12.3	11.0	12.5
Average return						
Per position	3.3	2.5	2.9	3.5	2.7	2.9
Per day	0.24	0.24	0.24	0.24	0.30	0.25
Average duration in days	14.1	10.7	12.0	14.5	9.2	11.4
Sum of losses	−73.1	−43.1	−62.1	−59.9	−36.9	−55.9
Unprofitable positions						
Number	29.1	24.3	27.8	20.8	20.8	22.6
Average return						
Per position	− 2.5	− 1.8	− 2.2	− 2.9	− 1.8	− 2.5
Per day	−0.48	−0.49	−0.51	−0.32	−0.46	−0.46
Average duration in days	5.3	3.6	4.3	9.0	3.9	5.4
Single rates of return						
Mean	−0.53	−0.28	−0.52	−0.50	−0.22	−0.57
t-statistic	−1.86	−1.22	−2.09	−1.33	−0.86	−1.89
Median	−0.71	−0.61	−0.80	−0.72	−0.72	−0.73
Standard deviation	3.76	2.76	3.22	4.31	2.87	3.57
Skewness	0.52	0.83	0.67	−0.11	1.12	0.67
Excess kurtosis	0.84	1.98	0.95	2.15	2.53	1.29
Sample size	176	149	167	132	127	140

1) UB1 = LB1 = 0.3. – 2) UB1 = LB1 = 0.3, UB2 = LB2 = 0.15. – 3) UB1 = LB1 = 0.4. – 4) UB1 = LB1 = 0.4, UB2 = LB2 = 0.2.

Table 6b: Pattern of technical trading in the DAX futures market, 30-minutes data, 1997-2000

	SG1	SG2[1])	SG3[1])	SG4[1])	SG5[1])	SG6[2])
Moving average models (MAS = 1, MAL = 15)						
Gross rate of return	47.4	40.2	41.3	41.4	44.4	44.0
Sum of profits	198.5	151.5	153.5	235.0	190.1	211.8
Profitable positions						
Number	165.6	124.5	168.1	274.8	227.5	256.8
Average return						
Per position	1.2	1.2	0.9	0.9	0.8	0.8
Per day	0.82	0.80	1.08	1.05	1.06	1.06
Average duration in days	1.5	1.5	0.9	0.8	0.8	0.8
Sum of losses	–151.1	–111.3	–112.2	–193.6	–145.7	–167.8
Unprofitable positions						
Number	373.5	188.7	320.2	467.2	413.1	448.7
Average return						
Per position	– 0.4	– 0.6	– 0.4	– 0.4	– 0.4	– 0.4
Per day	–1.24	–1.12	–1.47	–1.37	–1.52	–1.45
Average duration in days	0.3	0.5	0.2	0.3	0.2	0.3
Single rates of return						
Mean	0.09	0.13	0.09	0.06	0.07	0.06
t-statistic	3.81	3.70	4.09	3.23	3.89	3.64
Median	–0.18	–0.26	–0.13	–0.15	–0.13	–0.13
Standard deviation	1.07	1.23	0.91	0.94	0.90	0.91
Skewness	2.33	1.86	2.44	2.22	2.52	2.40
Excess kurtosis	10.55	5.91	11.27	12.19	14.73	13.92
Sample size	2,152	1,250	1,949	2,962	2,557	2,816
Momentum models (Time span = 12)						
Gross rate of return	49.3	49.8	48.6	48.9	49.1	48.7
Sum of profits	196.6	169.5	170.8	222.9	193.2	208.1
Profitable positions						
Number	183.9	134.3	203.4	294.4	251.8	275.3
Average return						
Per position	1.1	1.3	0.8	0.8	0.8	0.8
Per day	0.87	0.84	0.96	0.97	0.98	0.97
Average duration in days	1.2	1.5	0.9	0.8	0.8	0.8
Sum of losses	–147.2	–119.7	–122.2	–174.0	–144.1	–159.4
Unprofitable positions						
Number	317.4	209.7	288.9	420.4	359.3	390.3
Average return						
Per position	– 0.5	– 0.6	– 0.4	– 0.4	– 0.4	– 0.4
Per day	–1.05	–1.01	–1.27	–1.29	–1.29	–1.31
Average duration in days	0.4	0.6	0.3	0.3	0.3	0.3
Single rates of return						
Mean	0.10	0.15	0.10	0.07	0.08	0.07
t-statistic	3.71	3.96	4.16	3.70	4.01	3.82
Median	–0.15	–0.17	–0.09	–0.09	–0.09	–0.09
Standard deviation	1.19	1.35	1.05	0.99	0.99	0.99
Skewness	2.89	2.50	3.17	2.98	3.28	3.07
Excess kurtosis	18.41	14.37	26.27	26.62	27.89	27.20
Sample size	2,001	1,373	1,965	2,853	2,439	2,657
Relative strength models (Time span = 12)	SG4[1])	SG5[1])	SG6[2])	SG4[3])	SG5[3])	SG6[4])
Gross rate of return	23.7	36.7	32.7	6.9	28.33	20.2
Sum of profits	227.8	167.0	197.2	212.0	152.22	184.9
Profitable positions						
Number	286.1	246.5	273.8	249.5	229.48	244.0
Average return						
Per position	0.8	0.7	0.7	0.9	0.7	0.8
Per day	1.03	1.13	1.08	1.03	1.26	1.17
Average duration in days	0.8	0.6	0.7	0.8	0.5	0.7
Sum of losses	–204.1	–130.4	–164.5	–205.0	–123.89	–164.7
Unprofitable positions						
Number	390.6	346.5	370.3	350.0	325.18	347.7
Average return						
Per position	– 0.5	– 0.4	– 0.4	– 0.6	– 0.4	– 0.5
Per day	–1.43	–1.44	–1.49	–1.29	–1.54	–1.36
Average duration in days	0.4	0.3	0.3	0.5	0.3	0.4
Single rates of return						
Mean	0.04	0.06	0.05	0.01	0.05	0.03
t-statistic	1.78	3.58	2.80	0.53	2.93	1.75
Median	–0.09	–0.08	–0.08	–0.10	–0.09	–0.09
Standard deviation	1.03	0.84	0.92	1.08	0.82	0.95
Skewness	0.97	2.10	1.20	0.66	1.95	0.87
Excess kurtosis	8.85	12.20	12.60	7.78	12.35	11.54
Sample size	2,701	2,367	2,571	2,393	2,214	2,362

1) UB1 = LB1 = 0.3. – [2]) UB1 = LB1 = 0.3, UB2 = LB2 = 0.15. – [3]) UB1 = LB1 = 0.4. – [4]) UB1 = LB1 = 0.4, UB2 = LB2 = 0.2.

Table 7b: Pattern of technical trading in the DAX spot market, daily data, 1960-2000

		SG1	SG2[1])	SG3[1])	SG4[1])	SG5[1])	SG6[2])
Moving average models	MAS	1	2	1	12	5	1
	MAL	6	5	12	40	35	20
Gross rate of return		18.4	5.9	12.0	7.0	9.0	15.9
Sum of profits		47.6	36.8	34.6	20.7	22.9	34.3
Profitable positions							
Number		21.1	17.1	12.6	2.9	4.0	10.2
Average return							
Per position		2.3	2.2	2.7	7.0	5.8	3.4
Per day		0.19	0.19	0.15	0.09	0.09	0.13
Average duration in days		12.2	11.3	17.9	82.8	61.6	26.3
Sum of losses		–29.3	–31.0	–22.6	–13.7	–13.9	–18.4
Unprofitable positions							
Number		29.8	24.8	22.4	4.8	6.9	20.4
Average return							
Per position		– 1.0	– 1.3	– 1.0	– 2.9	– 2.0	– 0.9
Per day		–0.27	–0.27	–0.25	–0.11	–0.13	–0.21
Average duration in days		3.7	4.6	4.1	25.5	15.3	4.2
Single rates of return							
Mean		0.36	0.14	0.34	0.90	0.83	0.52
t-statistic		6.95	2.41	4.71	2.22	2.99	5.41
Median		–0.28	–0.32	–0.39	–1.00	–0.76	–0.40
Standard deviation		2.37	2.41	2.75	7.23	5.83	3.39
Skewness		2.57	1.69	2.73	2.37	2.96	3.65
Excess kurtosis		16.68	7.12	13.33	7.23	12.78	17.86
Sample size		2,086	1,718	1,434	315	443	1,254
Momentum models (time span)		5	18	13	3	35	28
Gross rate of return		14.0	11.9	9.8	13.5	8.9	9.8
Sum of profits		43.1	29.7	32.5	52.2	24.3	26.8
Profitable positions							
Number		17.8	7.8	10.6	30.0	6.4	8.4
Average return							
Per position		2.4	3.8	3.1	1.7	3.8	3.2
Per day		0.18	0.11	0.14	0.22	0.10	0.10
Average duration in days		13.4	33.2	22.3	8.1	39.8	32.8
Sum of losses		–29.1	–17.9	–22.7	–38.7	–15.4	–17.0
Unprofitable positions							
Number		26.7	11.8	17.5	39.6	10.9	12.3
Average return							
Per position		– 1.1	– 1.5	– 1.3	– 1.0	– 1.4	– 1.4
Per day		–0.23	–0.19	–0.22	–0.32	–0.15	–0.20
Average duration in days		4.7	8.1	5.9	3.1	9.6	7.0
Single rates of return							
Mean		0.32	0.60	0.35	0.19	0.51	0.47
t-statistic		5.21	3.91	3.34	5.15	2.74	3.12
Median		–0.27	–0.43	–0.44	–0.21	–0.41	–0.32
Standard deviation		2.58	4.38	3.54	2.01	4.97	4.40
Skewness		2.45	3.13	3.19	1.93	4.36	4.21
Excess kurtosis		14.24	14.12	14.99	9.73	25.41	24.31
Sample size		1,825	805	1,149	2,850	706	845
		SG4[1])	SG5[1])	SG6[2])	SG4[3])	SG5[3])	SG6[4])
Relative strength models (Time span)		13	14	28	9	26	11
Gross rate of return		2.6	8.0	5.0	4.2	4.7	6.9
Sum of profits		35.0	27.8	25.0	39.8	17.1	32.4
Profitable positions							
Number		14.4	12.5	7.9	16.9	6.8	13.9
Average return							
Per position		2.4	2.2	3.2	2.4	2.5	2.3
Per day		0.16	0.18	0.15	0.18	0.15	0.18
Average duration in days		15.6	12.3	20.7	13.1	16.3	12.9
Sum of losses		–32.5	–19.8	–20.0	–35.6	–12.4	–25.6
Unprofitable positions							
Number		20.7	17.0	11.8	21.6	8.8	18.8
Average return							
Per position		– 1.6	– 1.2	– 1.7	– 1.7	– 1.4	– 1.4
Per day		–0.23	–0.26	–0.18	–0.25	–0.23	–0.24
Average duration in days		6.8	4.6	9.5	6.7	6.2	5.7
Single rates of return							
Mean		0.07	0.27	0.25	0.11	0.30	0.21
t-statistic		0.92	3.60	1.96	1.49	2.66	2.92
Median		–0.33	–0.27	–0.39	–0.25	–0.22	–0.30
Standard deviation		3.00	2.61	3.64	2.91	2.87	2.63
Skewness		1.70	2.35	1.88	1.15	1.73	1.54
Excess kurtosis		7.91	10.09	7.14	6.98	6.34	5.40
Sample size		1,437	1,207	806	1,574	638	1,340

1) UB1 = LB1 = 0.3. – 2) UB1 = LB1 = 0.3, UB2 = LB2 = 0.15. – 3) UB1 = LB1 = 0.4. – 4) UB1 = LB1 = 0.4, UB2 = LB2=0.2.

Table 8b: Components of the profitability of technical trading by types of models
DAX spot market, daily data, 1960-2000

Signal generation	Profitable models	Models	Share of profitable models	Gross rate of return	t-statistic	Mean and standard deviation[1]) for each class of models					
						Profitable positions			Unprofitable positions		
						Number	Return per day	Duration in days	Number	Return per day	Duration in days
Moving average models											
SG 1	354	354	100.0	8.8	2.90	5.5	0.11	52.8	9.3	–0.15	15.2
				(2.3)	*(0.84)*	*(2.6)*	*(0.02)*	*(18.0)*	*(4.6)*	*(0.03)*	*(6.3)*
SG 2	354	354	100.0	8.3	2.81	4.9	0.11	54.4	7.8	–0.15	16.9
				(2.0)	*(0.72)*	*(2.2)*	*(0.02)*	*(18.1)*	*(3.7)*	*(0.03)*	*(6.9)*
SG 3	354	354	100.0	8.6	3.00	5.6	0.11	45.9	9.0	–0.16	13.8
				(2.3)	*(0.83)*	*(2.7)*	*(0.02)*	*(17.1)*	*(4.5)*	*(0.04)*	*(6.2)*
SG 4	354	354	100.0	9.1	3.02	6.7	0.11	44.7	11.2	–0.16	12.7
				(3.2)	*(1.13)*	*(3.6)*	*(0.02)*	*(17.0)*	*(5.7)*	*(0.04)*	*(5.7)*
SG 5	354	354	100.0	9.0	3.04	6.2	0.11	45.1	10.2	–0.16	12.9
				(2.7)	*(0.98)*	*(3.1)*	*(0.02)*	*(17.0)*	*(5.1)*	*(0.04)*	*(5.8)*
SG 6	354	354	100.0	9.1	3.04	6.4	0.11	44.8	10.7	–0.16	12.8
				(3.0)	*(1.06)*	*(3.3)*	*(0.02)*	*(17.1)*	*(5.5)*	*(0.04)*	*(5.7)*
Total	2124	2124	100.0	8.8	2.97	5.9	0.11	47.9	9.7	–0.16	14.1
				(2.6)	*(0.94)*	*(3.0)*	*(0.02)*	*(17.8)*	*(5.0)*	*(0.04)*	*(6.3)*
Momentum models											
SG 1	38	38	100.0	10.0	3.30	9.3	0.12	32.2	15.0	–0.18	8.1
				(1.8)	*(0.74)*	*(4.3)*	*(0.03)*	*(11.2)*	*(6.3)*	*(0.04)*	*(2.3)*
SG 2	38	38	100.0	9.6	3.21	8.2	0.12	35.5	13.3	–0.18	9.0
				(1.8)	*(0.72)*	*(3.8)*	*(0.03)*	*(12.8)*	*(5.6)*	*(0.04)*	*(2.6)*
SG 3	38	38	100.0	10.1	3.42	9.6	0.12	30.0	14.6	–0.19	7.6
				(1.8)	*(0.79)*	*(4.6)*	*(0.03)*	*(11.1)*	*(5.8)*	*(0.04)*	*(2.2)*
SG 4	38	38	100.0	10.9	3.62	11.7	0.12	25.9	17.6	–0.20	6.5
				(2.0)	*(0.82)*	*(5.4)*	*(0.03)*	*(9.0)*	*(7.0)*	*(0.04)*	*(1.8)*
SG 5	38	38	100.0	10.5	3.51	10.7	0.12	27.8	16.2	–0.20	7.0
				(1.9)	*(0.80)*	*(5.1)*	*(0.03)*	*(10.0)*	*(6.5)*	*(0.04)*	*(2.0)*
SG 6	38	38	100.0	10.7	3.57	11.2	0.12	26.8	16.9	–0.20	6.7
				(1.9)	*(0.82)*	*(5.3)*	*(0.03)*	*(9.5)*	*(6.8)*	*(0.04)*	*(1.9)*
Total	228	228	100.0	10.3	3.44	10.1	0.12	29.7	15.6	–0.19	7.5
				(1.9)	*(0.79)*	*(4.9)*	*(0.03)*	*(11.1)*	*(6.5)*	*(0.04)*	*(2.3)*
Relative strength models											
SG 4	46	76	60.5	2.3	0.81	10.6	0.14	30.2	15.1	–0.18	14.5
				(5.1)	*(1.90)*	*(7.6)*	*(0.04)*	*(20.5)*	*(8.4)*	*(0.07)*	*(9.4)*
SG 5	76	76	100.0	6.0	2.88	10.7	0.17	14.7	14.3	–0.24	5.6
				(3.1)	*(1.23)*	*(6.0)*	*(0.03)*	*(4.3)*	*(7.2)*	*(0.05)*	*(1.7)*
SG 6	67	76	88.2	4.8	1.93	11.0	0.15	20.7	15.7	–0.20	8.8
				(4.1)	*(1.66)*	*(6.8)*	*(0.03)*	*(10.0)*	*(7.4)*	*(0.06)*	*(4.1)*
Total	189	228	82.9	4.3	1.87	10.8	0.15	21.9	15.0	–0.21	9.6
				(4.4)	*(1.82)*	*(6.8)*	*(0.04)*	*(14.8)*	*(7.7)*	*(0.06)*	*(7.0)*
All models											
SG 1	392	392	100.0	9.0	2.94	5.8	0.11	50.8	9.8	–0.15	14.5
				(2.3)	*(0.84)*	*(3.0)*	*(0.02)*	*(18.5)*	*(5.1)*	*(0.03)*	*(6.4)*
SG 2	392	392	100.0	8.5	2.85	5.2	0.11	52.5	8.4	–0.15	16.2
				(2.0)	*(0.73)*	*(2.6)*	*(0.02)*	*(18.5)*	*(4.2)*	*(0.03)*	*(7.0)*
SG 3	392	392	100.0	8.8	3.04	6.0	0.11	44.4	9.6	–0.16	13.2
				(2.3)	*(0.84)*	*(3.1)*	*(0.02)*	*(17.3)*	*(4.9)*	*(0.04)*	*(6.2)*
SG 4	438	468	93.6	8.2	2.71	7.8	0.12	40.8	12.4	–0.17	12.5
				(4.4)	*(1.52)*	*(4.9)*	*(0.03)*	*(18.4)*	*(6.7)*	*(0.04)*	*(6.5)*
SG 5	468	468	100.0	8.6	3.05	7.3	0.12	38.7	11.4	–0.18	11.3
				(3.0)	*(1.02)*	*(4.3)*	*(0.03)*	*(19.1)*	*(6.0)*	*(0.05)*	*(5.9)*
SG 6	459	468	98.1	8.5	2.90	7.6	0.12	39.5	12.0	–0.17	11.7
				(3.5)	*(1.24)*	*(4.7)*	*(0.03)*	*(18.3)*	*(6.3)*	*(0.04)*	*(5.7)*
Total	2541	2580	98.5	8.6	2.91	6.7	0.12	44.0	10.7	–0.17	13.1
				(3.1)	*(1.09)*	*(4.1)*	*(0.03)*	*(19.1)*	*(5.8)*	*(0.04)*	*(6.5)*

[1]) In parentheses.

Table 9b: Components of 2,580 trading system by classes of the t-statistic and subperiods

DAX spot market, daily data, 1960-2000

t-statistic of the mean of the single returns	Number of models	Relative share in %	Gross rate of return	t-statistic	Mean for each class of models					
					Profitable positions			Unprofitable positions		
					Number	Return per day	Duration in days	Number	Return per day	Duration in days
1960-1971										
<0	20	0.8	–2.0	–0.41	5.1	0.10	42.6	8.1	–0.13	23.6
0-<1	42	1.6	3.1	0.65	6.4	0.12	32.0	10.0	–0.16	13.5
1-<2	434	16.8	8.5	1.70	6.2	0.12	42.3	8.4	–0.16	14.6
2-<3.0	1,651	64.0	12.8	2.53	5.9	0.11	50.5	8.1	–0.14	14.0
>3	433	16.8	17.9	3.68	11.5	0.14	29.5	16.4	–0.19	6.1
Total	2,580	100.0	12.6	2.53	6.9	0.11	45.3	9.6	–0.16	12.9
1972-1982										
<0	169	6.6	–1.3	–0.36	7.0	0.09	33.0	11.9	–0.14	12.7
0-<1	1,021	39.6	2.4	0.61	6.0	0.08	43.5	9.5	–0.12	15.8
1-<2	1,050	40.7	5.7	1.43	6.2	0.08	44.0	9.8	–0.12	13.2
2-<3.0	268	10.4	9.3	2.36	10.8	0.10	27.6	16.9	–0.15	6.3
>3	72	2.8	12.9	3.45	19.6	0.14	13.8	27.2	–0.20	3.7
Total	2,580	100.0	4.5	1.14	7.0	0.09	40.5	11.1	–0.13	13.2
1983-1991										
<0	49	1.9	–4.4	–0.75	5.5	0.13	35.7	10.4	–0.17	16.8
0-<1	1,063	41.2	5.1	0.67	5.2	0.14	49.9	9.3	–0.19	15.9
1-<2	1,213	47.0	10.6	1.40	7.1	0.15	39.9	12.4	–0.20	11.1
2-<3.0	255	9.9	16.4	2.19	9.3	0.15	33.6	17.1	–0.22	6.1
>3										
Total	2,580	100.0	8.6	1.14	6.5	0.14	43.3	11.5	–0.20	12.7
1992-2000										
<0	208	8.1	–4.0	–0.70	9.2	0.15	24.0	15.2	–0.24	11.1
0-<1	670	26.0	4.8	0.65	7.0	0.14	45.1	11.6	–0.21	14.3
1-<2	1,658	64.3	10.7	1.38	5.6	0.12	51.1	9.9	–0.18	14.0
2-<3.0	44	1.7	14.0	2.27	15.4	0.18	19.4	24.6	–0.28	4.6
>3										
Total	2,580	100.0	8.0	1.04	6.4	0.13	46.8	11.0	–0.19	13.7
1960-2000										
<0	39	1.5	–2.5	–0.99	4.7	0.10	44.6	8.5	–0.13	21.4
0-<1	39	1.5	1.7	0.66	7.5	0.14	25.4	12.1	–0.17	11.2
1-<2	207	8.0	4.6	1.63	8.2	0.14	26.1	12.4	–0.19	10.4
2-<3.0	1,314	50.9	7.6	2.54	5.3	0.11	51.3	8.1	–0.15	16.7
>3	981	38.0	11.4	3.93	8.3	0.12	38.8	13.9	–0.18	8.6
Total	2,580	100.0	8.6	2.91	6.7	0.12	44.0	10.7	–0.17	13.1

Table 10b: Pattern of technical trading in the DAX futures market, daily data, 1992-2000

		SG1	SG2[1])	SG3[1])	SG4[1])	SG5[1])	SG6[2])
Moving average models	MAS	1	2	1	12	5	1
	MAL	6	5	12	40	35	20
Gross rate of return		3.8	1.8	-0.1	-0.2	8.1	4.4
Sum of profits		51.4	41.5	35.1	21.7	25.5	34.3
Profitable positions							
Number		19.9	18.2	10.7	2.5	4.0	8.7
Average return							
Per position		2.6	2.3	3.3	8.7	6.5	3.9
Per day		0.22	0.22	0.17	0.10	0.10	0.15
Average duration in days		12.0	10.7	19.0	86.5	61.9	27.0
Sum of losses		–47.6	–39.8	–35.2	–21.9	–17.4	–30.0
Unprofitable positions							
Number		37.1	26.8	27.8	5.4	7.1	26.2
Average return							
Per position		– 1.3	– 1.5	– 1.3	– 4.0	– 2.5	– 1.1
Per day		–0.38	–0.34	–0.30	–0.15	–0.16	–0.25
Average duration in days		3.4	4.4	4.2	27.6	15.0	4.6
Single rates of return							
Mean		0.07	0.04	–0.00	–0.02	0.73	0.13
t-statistic		0.62	0.31	–0.02	–0.02	1.09	0.64
Median		–0.61	–0.44	–0.66	–1.70	–1.38	–0.67
Standard deviation		2.45	2.54	2.64	8.90	6.62	3.44
Skewness		1.74	1.28	1.67	1.83	3.07	4.24
Excess kurtosis		5.35	4.22	4.45	4.38	12.13	25.52
Sample size		512	404	345	70	98	312
Momentum models (time span)		5	18	13	3	35	28
Gross rate of return		7.3	10.0	0.7	1.5	7.2	3.1
Sum of profits		47.7	29.8	32.9	57.9	26.4	28.1
Profitable positions							
Number		17.6	7.5	10.8	31.1	8.0	7.2
Average return							
Per position		2.7	4.0	3.0	1.9	3.3	3.9
Per day		0.21	0.12	0.14	0.25	0.10	0.11
Average duration in days		13.2	33.3	21.5	7.5	32.9	35.6
Sum of losses		–40.4	–19.8	–32.2	–56.5	–19.2	–24.9
Unprofitable positions							
Number		30.6	12.4	20.4	45.5	12.5	15.2
Average return							
Per position		– 1.3	– 1.6	– 1.6	– 1.2	– 1.5	– 1.6
Per day		–0.31	–0.19	–0.29	–0.43	–0.20	–0.24
Average duration in days		4.3	8.5	5.6	2.9	7.6	6.9
Single rates of return							
Mean		0.15	0.50	0.02	0.02	0.35	0.14
t-statistic		1.19	1.53	0.10	0.23	0.99	0.39
Median		–0.46	–0.52	–0.52	–0.42	–0.37	–0.51
Standard deviation		2.64	4.39	3.64	2.13	4.78	5.06
Skewness		1.72	3.03	3.31	1.32	4.40	4.01
Excess kurtosis		4.81	12.84	17.02	3.63	24.68	22.73
Sample size		433	178	279	688	182	199
		SG4[1])	SG5[1])	SG6[2])	SG4[3])	SG5[3])	SG6[4])
Relative strength models (time span)		13	14	28	9	26	11
Gross rate of return		–15.9	– 1.4	–11.5	– 9.5	– 5.5	–10.0
Sum of profits		34.9	25.9	20.6	40.1	12.8	29.9
Profitable positions							
Number		13.4	12.4	6.1	16.5	5.1	14.2
Average return							
Per position		2.6	2.1	3.4	2.4	2.5	2.1
Per day		0.16	0.19	0.18	0.20	0.17	0.20
Average duration in days		16.0	11.3	19.3	12.4	14.6	10.5
Sum of losses		–50.8	–27.3	–32.0	–49.6	–18.2	–39.9
Unprofitable positions							
Number		25.2	19.5	16.1	25.2	10.9	22.7
Average return							
Per position		– 2.0	– 1.4	– 2.0	– 2.0	– 1.7	– 1.8
Per day		–0.34	–0.37	–0.23	–0.31	–0.28	–0.31
Average duration in days		6.0	3.8	8.8	6.4	6.0	5.7
Single rates of return							
Mean		–0.41	–0.04	–0.52	–0.23	–0.34	–0.27
t-statistic		–2.49	–0.31	–2.02	–1.42	–1.46	–1.83
Median		–0.64	–0.33	–0.87	–0.49	–0.68	–0.59
Standard deviation		3.08	2.40	3.59	3.10	2.78	2.68
Skewness		0.50	1.28	1.29	0.75	1.43	0.75
Excess kurtosis		2.37	3.44	7.81	4.52	4.11	3.35
Sample size		345	285	197	374	141	330

[1]) UB1 = LB1 = 0.3. – [2]) UB1 = LB1 = 0.3, UB2 = LB2 = 0.15. – [3]) UB1 = LB1 = 0.4. – [4]) UB1 = LB1 = 0.4, UB2 = LB2 = 0.2.

Table 11b: Components of the profitability of technical trading by types of models
DAX futures market, daily data 1992-2000

Signal generation	Profitable models	Models	Share of profitable models	Gross rate of return	Mean and standard deviation[2]) for each class of models						
					t-statistic	Profitable positions			Unprofitable positions		
						Number	Return per day	Duration in days	Number	Return per day	Duration in days
Moving average models											
SG 1	330	354	93.2	5.6	0.74	5.3	0.12	53.2	10.1	–0.18	15.7
				(3.5)	*(0.47)*	*(2.7)*	*(0.02)*	*(19.5)*	*(5.4)*	*(0.05)*	*(7.2)*
SG 2	333	354	94.1	5.3	0.72	4.7	0.12	55.4	8.7	–0.17	17.3
				(3.1)	*(0.43)*	*(2.4)*	*(0.02)*	*(19.6)*	*(4.3)*	*(0.05)*	*(7.5)*
SG 3	336	354	94.9	5.2	0.74	5.4	0.12	46.8	9.9	–0.19	14.3
				(2.9)	*(0.42)*	*(2.7)*	*(0.02)*	*(17.6)*	*(5.3)*	*(0.05)*	*(6.4)*
SG 4	320	354	90.4	5.3	0.70	6.4	0.12	45.0	12.1	–0.20	13.0
				(3.8)	*(0.52)*	*(3.4)*	*(0.02)*	*(16.9)*	*(6.8)*	*(0.06)*	*(6.1)*
SG 5	328	354	92.7	5.4	0.74	5.9	0.12	45.8	11.1	–0.19	13.3
				(3.3)	*(0.46)*	*(3.0)*	*(0.02)*	*(17.5)*	*(6.1)*	*(0.05)*	*(6.1)*
SG 6	323	354	91.2	5.3	0.72	6.2	0.12	45.3	11.6	–0.20	13.1
				(3.5)	*(0.49)*	*(3.2)*	*(0.02)*	*(17.3)*	*(6.5)*	*(0.05)*	*(6.0)*
Total	1,970	2,124	92.7	5.3	0.72	5.7	0.12	48.6	10.6	–0.19	14.5
				(3.4)	*(0.46)*	*(3.0)*	*(0.02)*	*(18.5)*	*(5.9)*	*(0.05)*	*(6.8)*
Momentum models											
SG 1	33	38	86.8	4.6	0.63	9.5	0.13	30.4	17.1	–0.24	7.4
				(4.2)	*(0.61)*	*(4.4)*	*(0.03)*	*(10.3)*	*(7.4)*	*(0.05)*	*(2.0)*
SG 2	33	38	86.8	4.5	0.62	8.5	0.13	33.3	15.2	–0.23	8.2
				(4.3)	*(0.63)*	*(4.0)*	*(0.03)*	*(11.7)*	*(6.6)*	*(0.05)*	*(2.2)*
SG 3	34	38	89.5	4.5	0.62	9.9	0.13	28.3	16.8	–0.25	7.0
				(4.0)	*(0.58)*	*(4.7)*	*(0.04)*	*(10.3)*	*(6.9)*	*(0.06)*	*(2.0)*
SG 4	33	38	86.8	4.6	0.63	11.9	0.14	24.8	20.3	–0.26	6.0
				(3.8)	*(0.53)*	*(5.4)*	*(0.04)*	*(8.4)*	*(8.2)*	*(0.06)*	*(1.6)*
SG 5	34	38	89.5	4.6	0.63	10.9	0.14	26.3	18.6	–0.25	6.5
				(3.9)	*(0.55)*	*(5.0)*	*(0.04)*	*(9.3)*	*(7.6)*	*(0.06)*	*(1.8)*
SG 6	32	38	84.2	4.6	0.63	11.4	0.14	25.5	19.5	–0.26	6.2
				(3.9)	*(0.56)*	*(5.2)*	*(0.04)*	*(8.9)*	*(7.9)*	*(0.06)*	*(1.7)*
Total	199	228	87.3	4.6	0.63	10.3	0.13	28.1	17.9	–0.25	6.9
				(4.0)	*(0.57)*	*(4.9)*	*(0.04)*	*(10.2)*	*(7.6)*	*(0.06)*	*(2.0)*
Relative strength models											
SG 4	5	76	6.6	–10.1	–1.62	10.1	0.14	31.3	17.2	–0.22	19.6
				(5.2)	*(0.83)*	*(8.2)*	*(0.05)*	*(23.3)*	*(10.5)*	*(0.11)*	*(21.5)*
SG 5	15	76	19.7	– 3.0	–0.69	10.2	0.18	13.3	16.6	–0.33	5.2
				(3.7)	*(0.79)*	*(6.1)*	*(0.04)*	*(4.4)*	*(9.0)*	*(0.07)*	*(1.8)*
SG 6	6	76	7.9	– 7.0	–1.28	10.6	0.16	20.5	18.6	–0.28	8.0
				(4.4)	*(0.81)*	*(7.0)*	*(0.05)*	*(12.4)*	*(9.3)*	*(0.09)*	*(3.4)*
Total	26	228	11.4	– 6.7	–1.20	10.3	0.16	21.7	17.5	–0.27	10.9
				(5.3)	*(0.90)*	*(7.1)*	*(0.05)*	*(17.1)*	*(9.6)*	*(0.10)*	*(14.0)*
All models											
SG 1	363	392	92.6	5.5	0.73	5.7	0.12	51.0	10.8	–0.19	14.9
				(3.6)	*(0.49)*	*(3.1)*	*(0.02)*	*(20.0)*	*(6.0)*	*(0.05)*	*(7.3)*
SG 2	366	392	93.4	5.2	0.71	5.1	0.12	53.3	9.4	–0.18	16.4
				(3.2)	*(0.45)*	*(2.8)*	*(0.02)*	*(20.1)*	*(5.0)*	*(0.05)*	*(7.7)*
SG 3	370	392	94.4	5.2	0.73	5.8	0.12	45.0	10.6	–0.19	13.6
				(3.1)	*(0.44)*	*(3.2)*	*(0.02)*	*(17.9)*	*(5.9)*	*(0.06)*	*(6.5)*
SG 4	358	468	76.5	2.7	0.32	7.5	0.13	41.1	13.6	–0.21	13.5
				(6.9)	*(1.03)*	*(5.0)*	*(0.03)*	*(18.9)*	*(8.1)*	*(0.07)*	*(10.6)*
SG 5	377	468	80.6	4.0	0.50	7.0	0.13	38.9	12.6	–0.22	11.5
				(4.6)	*(0.75)*	*(4.3)*	*(0.03)*	*(19.9)*	*(7.3)*	*(0.08)*	*(6.3)*
SG 6	361	468	77.1	3.2	0.38	7.3	0.13	39.7	13.4	–0.21	11.7
				(5.8)	*(0.92)*	*(4.7)*	*(0.03)*	*(18.9)*	*(7.8)*	*(0.07)*	*(6.0)*
Total	2195	2580	85.1	4.2	0.55	6.5	0.13	44.4	11.8	–0.20	13.5
				(5.0)	*(0.76)*	*(4.1)*	*(0.03)*	*(20.0)*	*(7.0)*	*(0.07)*	*(7.8)*

[2]) In parentheses.

Table 12b: Components of 2,580 trading system by classes of the t-statistic and subperiods

DAX futures market, daily data, 1992-2000

t-statistic of the mean of the single returns	Number of models	Relative share of profitable models	Gross rate of return	t-statistic	Mean for each class of models					
					Profitable positions			Unprofitable positions		
					Number	Return per day	Duration in days	Number	Return per day	Duration in days
1992-1994										
<0	1,202	46.6	–3.2	–0.39	7.5	0.10	36.4	15.1	–0.18	12.3
0-<1	1,315	51.0	2.7	0.33	6.2	0.09	42.4	10.8	–0.15	15.5
1-<2	63	2.4	10.2	1.15	7.1	0.10	36.7	8.2	–0.15	12.7
2-<3.0										
Total	2,580	100.0	0.1	0.01	6.8	0.10	39.5	12.7	–0.16	13.9
1995-1997										
<0	303	11.7	–8.1	–1.05	11.2	0.14	17.8	21.4	–0.25	9.7
0-<1	1,422	55.1	6.8	0.62	5.8	0.11	52.8	10.3	–0.18	14.5
1-<2	853	33.1	14.3	1.28	6.0	0.12	44.2	9.3	–0.16	12.2
2-<3.0	2	0.1	22.3	2.27	7.9	0.15	28.8	5.7	–0.16	11.2
Total	2,580	100.0	7.5	0.64	6.5	0.12	45.8	11.3	–0.18	13.2
1998-2000										
<0	567	22.0	–8.1	–0.66	7.7	0.17	34.5	15.0	–0.32	11.3
0-<1	1,919	74.4	7.9	0.46	5.4	0.16	52.2	10.6	–0.24	13.8
1-<2	89	3.4	18.6	1.36	16.8	0.23	19.8	21.5	–0.43	5.7
2-<3.0	5	0.2	30.7	2.32	23.9	0.31	10.2	27.8	–0.51	2.9
Total	2,580	100.0	4.8	0.25	6.3	0.17	47.1	12.0	–0.27	12.9
1992-2000										
<0	384	14.9	–5.2	–0.92	9.2	0.15	25.0	16.8	–0.26	10.4
0-<1	1,494	57.9	4.4	0.61	6.0	0.12	49.4	11.5	–0.20	14.2
1-<2	702	27.2	8.9	1.21	6.0	0.12	44.4	9.9	–0.18	13.6
2-<3.0										
Total	2,580	100.0	4.2	0.55	6.5	0.13	44.4	11.8	–0.20	13.5

Table 13b: Pattern of profitability of 2,580 trading systems by classes of the t-statistic

Comparison between trading in the DAX 500 spot and futures market, 1983-2000

t-statistic of the mean of the single returns	Number of models	Relative share in %	Gross rate of return	t-statistic	Mean and standard deviation[3]) for each class of models					
					Profitable positions			Unprofitable positions		
					Number	Return per day	Duration in days	Number	Return per day	Duration in days
Spot market										
<0	208	8.1	–4.0	–0.70	9.2	0.15	24.0	15.2	–0.24	11.1
			(3.4)	*(0.58)*	*(4.5)*	*(0.03)*	*(14.6)*	*(6.4)*	*(0.08)*	*(8.4)*
0-<1	670	26.0	4.8	0.65	7.0	0.14	45.1	11.6	–0.21	14.3
			(2.3)	*(0.26)*	*(4.1)*	*(0.02)*	*(28.8)*	*(6.0)*	*(0.06)*	*(8.8)*
1-<2	1,658	64.3	10.7	1.38	5.6	0.12	51.1	9.9	–0.18	14.0
			(1.7)	*(0.21)*	*(3.5)*	*(0.02)*	*(15.9)*	*(5.8)*	*(0.05)*	*(6.4)*
2-<3.0	44	1.7	14.0	2.27	15.4	0.18	19.4	24.6	–0.28	4.6
			(1.2)	*(0.22)*	*(6.0)*	*(0.04)*	*(9.1)*	*(8.8)*	*(0.05)*	*(1.4)*
Total	2,580	100.0	8.0	1.04	6.4	0.13	46.8	11.0	–0.19	13.7
			(4.9)	*(0.68)*	*(4.1)*	*(0.03)*	*(21.5)*	*(6.4)*	*(0.06)*	*(7.3)*
Futures market										
<0	384	14.9	–5.2	–0.92	9.2	0.15	25.0	16.8	–0.26	10.4
			(4.3)	*(0.75)*	*(4.9)*	*(0.04)*	*(17.0)*	*(7.6)*	*(0.08)*	*(11.3)*
0-<1	1,494	57.9	4.4	0.61	6.0	0.12	49.4	11.5	–0.20	14.2
			(2.0)	*(0.26)*	*(4.0)*	*(0.03)*	*(20.6)*	*(7.0)*	*(0.06)*	*(7.6)*
1-<2	702	27.2	8.9	1.21	6.0	0.12	44.4	9.9	–0.18	13.6
			(1.3)	*(0.16)*	*(3.2)*	*(0.02)*	*(12.2)*	*(5.4)*	*(0.05)*	*(4.9)*
2-<3.0	–	–	–	–	–	–	–	–	–	–
			–	–	–	–	–	–	–	–
Total	2,580	100.0	4.2	0.55	6.5	0.13	44.4	11.8	–0.20	13.5
			(5.0)	*(0.76)*	*(4.1)*	*(0.03)*	*(20.0)*	*(7.0)*	*(0.07)*	*(7.8)*

[3]) In parentheses.

Table 15b: Pattern of technical trading in the DAX futures market, 30-minutes-data, 1997-2000

		SG1	SG2[1])	SG3[1])	SG4[1])	SG5[1])	SG6[2])
Moving average models	MAS	1	2	1	12	5	1
	MAL	6	5	12	40	35	20
Gross rate of return		39.0	12.0	26.1	8.4	20.5	57.7
Sum of profits		265.7	115.1	150.6	109.6	114.4	193.4
Profitable positions							
Number		335.5	145.2	190.7	62.1	75.1	214.9
Average return							
Per position		0.8	0.8	0.8	1.8	1.5	0.9
Per day		1.20	1.41	1.19	0.48	0.55	0.84
Average duration in days		0.7	0.6	0.7	3.7	2.8	1.1
Sum of losses		– 226.7	– 103.1	– 124.5	– 101.2	– 93.9	– 135.7
Unprofitable positions							
Number		669.2	203.6	352.3	93.7	127.2	372.8
Average return							
Per position		– 0.3	– 0.5	– 0.4	– 1.1	– 0.7	– 0.4
Per day		– 1.58	– 2.04	– 1.73	– 0.74	– 0.89	– 1.44
Average duration in days		0.2	0.3	0.2	1.5	0.8	0.3
Single rates of return							
Mean		0.04	0.03	0.05	0.05	0.10	0.10
t-statistic		2.99	1.30	2.66	0.71	1.86	4.76
Median		– 0.13	– 0.10	– 0.12	– 0.33	– 0.27	– 0.12
Standard deviation		0.82	0.99	0.84	1.89	1.54	1.00
Skewness		1.90	0.54	2.01	1.45	1.98	3.20
Excess kurtosis		14.30	11.34	12.33	3.46	6.38	23.00
Sample size		4,010	1,391	2,167	620	805	2,344
Momentum models (time span)		5	18	13	3	35	28
Gross rate of return		32.5	23.4	53.4	18.1	28.8	28.1
Sum of profits		244.7	135.0	170.4	299.8	123.8	149.3
Profitable positions							
Number		313.4	99.8	193.4	536.9	120.8	157.5
Average return							
Per position		0.8	1.4	0.9	0.6	1.0	1.0
Per day		1.10	0.63	0.93	1.46	0.52	0.61
Average duration in days		0.7	2.2	1.0	0.4	2.0	1.5
Sum of losses		– 212.2	– 111.6	– 117.0	– 281.7	– 95.1	– 121.2
Unprofitable positions							
Number		561.5	173.5	274.4	683.4	201.0	258.8
Average return							
Per position		– 0.4	– 0.6	– 0.4	– 0.4	– 0.5	– 0.5
Per day		– 1.48	– 0.94	– 1.33	– 1.76	– 0.93	– 1.14
Average duration in days		0.3	0.7	0.3	0.2	0.5	0.4
Single rates of return							
Mean		0.04	0.09	0.11	0.02	0.09	0.07
t-statistic		2.51	1.99	4.58	1.41	2.54	2.28
Median		– 0.11	– 0.25	– 0.09	– 0.08	– 0.14	– 0.11
Standard deviation		0.87	1.43	1.08	0.73	1.26	1.21
Skewness		1.30	2.35	3.20	1.16	2.70	2.65
Excess kurtosis		12.18	10.50	22.06	12.20	13.37	16.37
Sample size		3,492	1,090	1,867	4,871	1,281	1,660
		SG4[1])	SG5[1])	SG6[2])	SG4[3])	SG5[3])	SG6[4])
Relative strength models (time span)		13	14	28	9	26	11
Gross rate of return		57.3	47.6	9.8	15.8	9.9	25.3
Sum of profits		234.0	164.4	134.3	239.1	96.2	197.1
Profitable positions							
Number		278.6	223.8	141.9	325.2	108.6	275.4
Average return							
Per position		0.8	0.7	1.0	0.7	0.9	0.7
Per day		1.04	1.09	0.82	1.10	0.95	1.13
Average duration in days		0.8	0.7	1.2	0.7	0.9	0.6
Sum of losses		– 176.7	– 116.9	– 124.5	– 223.3	– 86.3	– 171.8
Unprofitable positions							
Number		350.5	302.9	231.4	434.2	187.6	365.1
Average return							
Per position		– 0.5	– 0.4	– 0.5	– 0.5	– 0.5	– 0.5
Per day		– 1.27	– 1.31	– 1.12	– 1.52	– 1.28	– 1.52
Average duration in days		0.4	0.3	0.5	0.3	0.4	0.3
Single rates of return							
Mean		0.09	0.09	0.03	0.02	0.03	0.04
t-statistic		4.31	4.72	0.89	1.20	1.15	2.15
Median		– 0.07	– 0.07	– 0.12	– 0.08	– 0.13	– 0.08
Standard deviation		1.06	0.88	1.14	0.96	1.00	0.93
Skewness		1.32	2.17	2.24	0.81	2.26	0.86
Excess kurtosis		9.08	9.85	14.64	9.74	12.32	11.02
Sample size		2,511	2,102	1,489	3,031	1,181	2,556

[1]) UB1 = LB1 = 0.3. – [2]) UB1 = LB1 = 0.3, UB2 = LB2 = 0.15. – [3]) UB1 = LB1 = 0.4. – [4]) UB1 = LB1 = 0.4, UB2 = LB2 = 0.2.

Table 16b: Components of the profitability of technical trading by types of models
DAX futures market, 30-minutes-data, 1997-2000

Signal generation	Profitable models	Number of models	Share of profitable models	Gross rate of return	Net rate of return	t-statistic	Mean and standard deviation[4]) for each class of models					
							Profitable positions			Unprofitable positions		
							Number	Return per day	Duration in days	Number	Return per day	Duration in days
Moving average models												
SG 1	354	354	100.0	26.1	20.8	2.1	93.84	0.60	2.9	167.77	–0.90	0.9
				(11.7)	*(10.5)*	*(0.9)*	*(43.10)*	*(0.13)*	*(1.0)*	*(86.67)*	*(0.18)*	*(0.3)*
SG 2	354	354	100.0	21.1	17.6	2.0	68.48	0.58	3.1	101.56	–0.89	1.1
				(8.2)	*(7.6)*	*(0.7)*	*(24.57)*	*(0.15)*	*(1.1)*	*(36.74)*	*(0.20)*	*(0.4)*
SG 3	354	354	100.0	21.8	17.3	2.3	90.32	0.75	1.9	134.35	–1.14	0.7
				(8.0)	*(7.3)*	*(0.8)*	*(34.17)*	*(0.28)*	*(0.9)*	*(65.28)*	*(0.35)*	*(0.3)*
SG 4	346	354	97.7	23.6	17.2	1.9	129.63	0.70	2.0	185.81	–0.96	0.9
				(14.9)	*(14.3)*	*(1.2)*	*(59.88)*	*(0.18)*	*(0.8)*	*(94.96)*	*(0.19)*	*(0.3)*
SG 5	353	354	99.7	24.8	18.9	2.3	112.71	0.74	1.9	175.78	–1.06	0.7
				(11.7)	*(10.7)*	*(1.0)*	*(51.55)*	*(0.23)*	*(0.8)*	*(88.38)*	*(0.24)*	*(0.3)*
SG 6	352	354	99.4	25.0	18.8	2.1	121.84	0.72	2.0	183.90	–1.00	0.8
				(12.5)	*(11.8)*	*(1.0)*	*(56.97)*	*(0.20)*	*(0.8)*	*(93.90)*	*(0.21)*	*(0.3)*
Total	2,113	2,124	99.5	23.7	18.4	2.1	102.80	0.68	2.3	158.20	–0.99	0.8
				(11.6)	*(10.7)*	*(1.0)*	*(51.13)*	*(0.21)*	*(1.0)*	*(85.90)*	*(0.25)*	*(0.4)*
Momentum models												
SG 1	38	38	100.0	29.0	20.2	2.3	154.55	0.69	1.9	281.20	–1.05	0.5
				(12.2)	*(11.3)*	*(0.9)*	*(80.86)*	*(0.23)*	*(0.7)*	*(140.00)*	*(0.22)*	*(0.1)*
SG 2	38	38	100.0	25.5	19.5	2.2	108.51	0.68	2.4	184.98	–0.99	0.7
				(10.6)	*(10.1)*	*(0.9)*	*(52.68)*	*(0.26)*	*(1.0)*	*(83.96)*	*(0.24)*	*(0.2)*
SG 3	38	38	100.0	26.7	18.4	2.4	161.41	0.77	1.5	251.32	–1.21	0.4
				(10.1)	*(10.0)*	*(0.9)*	*(76.87)*	*(0.32)*	*(0.7)*	*(93.31)*	*(0.35)*	*(0.1)*
SG 4	38	38	100.0	28.9	16.8	2.3	235.18	0.77	1.2	363.67	–1.24	0.4
				(12.4)	*(13.9)*	*(1.0)*	*(104.21)*	*(0.25)*	*(0.5)*	*(134.72)*	*(0.23)*	*(0.1)*
SG 5	38	38	100.0	28.9	18.4	2.5	201.67	0.77	1.3	317.66	–1.24	0.4
				(11.1)	*(11.3)*	*(0.9)*	*(98.97)*	*(0.29)*	*(0.6)*	*(131.04)*	*(0.30)*	*(0.1)*
SG 6	38	38	100.0	28.9	17.6	2.4	219.20	0.78	1.3	344.66	–1.25	0.4
				(12.0)	*(12.8)*	*(1.0)*	*(102.72)*	*(0.27)*	*(0.5)*	*(138.01)*	*(0.27)*	*(0.1)*
Total	228	228	100.0	28.0	18.5	2.4	180.09	0.74	1.6	290.58	–1.17	0.5
				(11.4)	*(11.6)*	*(0.9)*	*(97.13)*	*(0.27)*	*(0.8)*	*(135.17)*	*(0.29)*	*(0.2)*
Relative strength models												
SG 4	47	76	61.8	8.3	–1.8	0.6	199.24	0.86	1.5	301.83	–1.07	0.8
				(17.8)	*(14.8)*	*(1.4)*	*(134.09)*	*(0.23)*	*(0.8)*	*(176.97)*	*(0.38)*	*(0.5)*
SG 5	72	76	94.7	18.5	9.0	1.9	186.40	1.01	0.8	284.68	–1.39	0.3
				(13.9)	*(11.7)*	*(1.3)*	*(109.08)*	*(0.18)*	*(0.3)*	*(155.77)*	*(0.28)*	*(0.1)*
SG 6	59	76	77.6	14.0	3.8	1.2	197.01	0.94	1.1	306.47	–1.23	0.5
				(16.5)	*(14.1)*	*(1.4)*	*(121.17)*	*(0.20)*	*(0.5)*	*(163.99)*	*(0.33)*	*(0.2)*
Total	178	228	78.1	13.6	3.7	1.2	194.21	0.94	1.1	297.66	–1.23	0.5
				(16.6)	*(14.3)*	*(1.5)*	*(121.47)*	*(0.22)*	*(0.6)*	*(165.34)*	*(0.36)*	*(0.3)*
All models												
SG 1	392	392	100.0	26.4	20.8	2.1	99.73	0.61	2.8	178.76	–0.91	0.9
				(11.8)	*(10.6)*	*(0.9)*	*(51.18)*	*(0.15)*	*(1.0)*	*(98.82)*	*(0.19)*	*(0.3)*
SG 2	392	392	100.0	21.5	17.8	2.0	72.36	0.59	3.0	109.65	–0.90	1.0
				(8.5)	*(7.9)*	*(0.8)*	*(30.79)*	*(0.16)*	*(1.1)*	*(49.96)*	*(0.21)*	*(0.4)*
SG 3	392	392	100.0	22.3	17.4	2.3	97.21	0.75	1.9	145.69	–1.15	0.6
				(8.4)	*(7.6)*	*(0.8)*	*(45.35)*	*(0.29)*	*(0.9)*	*(76.63)*	*(0.35)*	*(0.3)*
SG 4	431	468	92.1	21.5	14.1	1.7	149.50	0.73	1.9	219.09	–1.00	0.8
				(16.3)	*(15.9)*	*(1.3)*	*(88.08)*	*(0.20)*	*(0.8)*	*(130.15)*	*(0.25)*	*(0.4)*
SG 5	463	468	98.9	24.1	17.3	2.2	131.90	0.79	1.7	204.99	–1.13	0.6
				(12.3)	*(11.5)*	*(1.1)*	*(76.52)*	*(0.25)*	*(0.8)*	*(117.79)*	*(0.29)*	*(0.3)*
SG 6	449	468	95.9	23.5	16.3	2.0	141.95	0.76	1.8	216.86	–1.06	0.7
				(13.9)	*(13.4)*	*(1.2)*	*(83.26)*	*(0.22)*	*(0.8)*	*(126.30)*	*(0.26)*	*(0.3)*
Total	2,519	2,580	97.6	23.2	17.1	2.1	117.71	0.71	2.1	182.22	–1.03	0.8
				(12.5)	*(11.9)*	*(1.1)*	*(72.97)*	*(0.23)*	*(1.0)*	*(113.05)*	*(0.28)*	*(0.4)*

[4]) In parentheses.

Table 17b: Components of 2,580 trading systems by classes of the t-statistic and subperiods

DAX futures market, 30-minutes-data, 1997-2000

t-statistic of the mean of the single returns	Number of models	Share of profitable models	Gross rate of return	Net rate of return	t-statistic	Mean for each class of models					
						Profitable positions			Unprofitable positions		
						Number	Return per day	Duration in days	Number	Return per day	Duration in days
1997											
<0	125	4.8	–22.9	–32.2	–0.95	188.9	0.93	0.9	271.3	–1.27	0.6
0-<1	245	9.5	12.7	3.7	0.57	178.6	0.87	1.3	267.4	–1.17	0.6
1-<2	1,095	42.4	33.3	28.4	1.61	97.7	0.59	2.7	140.6	–0.82	1.0
2-<3.0	1,030	39.9	48.0	43.2	2.38	101.1	0.65	2.3	134.0	–0.89	0.8
>3	85	3.3	69.4	63.0	3.17	136.3	0.76	1.6	182.2	–1.00	0.6
Total	2,580	100.0	35.7	30.2	1.75	112.4	0.66	2.3	157.7	–0.91	0.8
1998											
<0	116	4.5	–10.1	–17.5	–0.37	138.1	0.92	1.9	227.6	–1.20	0.9
0-<1	869	33.7	17.1	11.7	0.64	102.0	0.76	2.7	162.3	–1.08	1.0
1-<2	1,057	41.0	39.8	34.1	1.46	108.7	0.82	2.2	170.6	–1.09	0.8
2-<3.0	493	19.1	67.3	61.3	2.37	121.8	0.87	1.8	176.6	–1.11	0.7
>3	45	1.7	94.3	85.9	3.29	173.7	1.01	1.3	241.8	–1.20	0.5
Total	2,580	100.0	36.1	30.4	1.31	111.4	0.82	2.3	172.7	–1.10	0.9
1999											
<0	1,343	52.1	–15.2	–20.4	–0.71	88.6	0.59	2.2	165.2	–0.99	0.8
0-<1	900	34.9	9.1	2.7	0.43	116.7	0.66	2.3	201.5	–1.02	0.8
1-<2	306	11.9	30.1	19.8	1.42	215.3	0.96	1.0	299.6	–1.31	0.4
2-<3.0	31	1.2	48.3	38.9	2.22	212.8	1.00	0.9	250.3	–1.21	0.6
>3	–	–	–	–	–	–	–	–	–	–	–
Total	2,580	100.0	–0.6	–6.8	–0.03	115.0	0.67	2.1	194.9	–1.04	0.8
2000											
<0	430	16.7	–8.6	–13.4	–0.40	89.6	0.54	2.4	143.1	–0.99	0.9
0-<1	932	36.1	10.6	4.8	0.50	112.9	0.63	2.2	169.4	–1.06	0.7
1-<2	964	37.4	31.5	23.3	1.47	161.8	0.81	1.5	245.7	–1.24	0.5
2-<3.0	254	9.8	49.6	38.5	2.28	214.9	0.91	1.1	337.8	–1.42	0.3
>3	–	–	–	–	–	–	–	–	–	–	–
Total	2,580	100.0	19.0	12.0	0.89	137.3	0.71	1.8	210.1	–1.15	0.6
1997-2000											
<0	61	2.4	–6.3	–12.7	–0.51	121.0	0.77	1.7	198.7	–0.94	0.9
0-<1	316	12.2	7.5	2.1	0.66	107.3	0.68	2.3	159.1	–0.97	1.0
1-<2	931	36.1	16.9	11.8	1.51	98.7	0.63	2.6	152.7	–0.95	0.9
2-<3.0	743	28.8	27.8	21.4	2.47	123.8	0.74	2.0	193.0	–1.08	0.7
>3	529	20.5	40.7	33.1	3.54	148.5	0.82	1.4	230.9	–1.15	0.5
Total	2,580	100.0	23.2	17.1	2.05	117.7	0.71	2.1	182.2	–1.03	0.8

Table 18b: Distribution of technical trading systems by the ratio of the profit components

DAX futures market, 30-minutes-data, 1997-2000

	NPP/NPL			RPP/RPL			DRP/DRL			DPP/DPL		
t-statistic of the mean of the single returns	<0.8	0.8-1.0	>1	<2	2.0-3.0	>3	<0.7	0.7-0.8	>0.8	<2.5	2.5-4	>4
Moving average models												
<0	95.2	4.5	0.3	93.2	6.7	0.2	86.9	7.7	5.5	46.4	50.4	3.2
0-<1	86.3	12.3	1.4	82.4	17.2	0.5	66.0	22.0	12.0	40.0	54.6	5.4
1-<2	71.2	24.4	4.4	67.0	30.8	2.1	51.8	26.2	22.0	40.2	51.7	8.1
2-<3.0	53.0	34.4	12.6	53.7	42.1	4.1	42.6	25.8	31.6	38.6	50.6	10.8
>3	57.0	35.5	7.6	55.1	39.2	5.7	36.0	32.5	31.5	44.9	39.1	16.1
Total	73.0	21.7	5.2	70.5	27.4	2.1	56.9	22.9	20.2	40.9	51.3	7.8
Momentum models												
<0	100.0	-	-	88.3	11.7	-	89.1	6.1	4.8	12.7	77.1	10.2
0-<1	100.0	-	-	59.8	40.2	-	79.5	14.5	6.0	19.9	55.6	24.5
1-<2	99.3	0.7	-	40.2	59.6	0.2	78.5	17.0	4.5	11.5	67.9	20.6
2-<3.0	98.2	1.8	-	37.6	62.0	0.4	67.1	26.5	6.4	6.2	85.9	7.9
>3	90.3	9.7	-	18.4	80.4	1.1	30.6	51.0	18.4	1.3	98.7	-
			-									
Total	98.7	1.3	-	46.5	53.3	0.2	73.6	20.0	6.3	12.1	70.8	17.0
Relative strength models												
<0	100.0	-	-	94.7	5.3	-	41.1	23.8	35.1	74.7	24.7	0.7
0-<1	100.0	-	-	88.9	10.9	0.2	34.5	31.9	33.6	69.2	30.2	0.6
1-<2	96.3	3.7	-	85.2	14.8	-	25.5	41.2	33.3	67.8	32.0	0.2
2-<3.0	90.6	9.4	-	81.2	18.8	-	20.4	42.7	36.8	71.7	28.3	-
>3	86.5	13.5	-	76.9	23.1	-	9.6	45.3	45.2	75.3	24.7	-
			-									
Total	97.2	2.8	-	87.9	12.1	0.1	30.8	34.5	34.7	70.7	28.9	0.4
All models												
<0	96.1	3.6	0.3	93.2	6.6	0.1	80.0	10.0	10.0	49.5	47.4	3.1
0-<1	88.9	10.0	1.1	80.9	18.7	0.4	64.2	22.3	13.6	41.0	52.3	6.7
1-<2	75.6	20.7	3.7	66.0	32.3	1.8	52.3	26.5	21.3	39.7	51.7	8.6
2-<3.0	57.9	31.0	11.2	53.7	42.6	3.7	43.4	26.6	30.0	37.7	52.2	10.1
>3	62.6	31.2	6.2	52.5	42.7	4.8	33.7	35.4	30.9	42.0	44.8	13.2
Total	77.1	18.5	4.4	70.0	28.2	1.8	56.1	23.7	20.3	41.0	51.0	8.0

NPP (NPL) . . . Number of profitable (unprofitable) positions per year.
RPP (RPL) . . . Average return per profitable (unprofitable) position.
DRP (DRL) . . . Retern per day during profitable (unprofitable) positions.
DPP (DPL) . . . Average duration of profitable (unprofitable) positions.

The rations are calculated in absolute terms, i.e., the negative sign of returns of unprofitable positions is neglected.

Table 19b: Cluster of 2,580 trading systems according to profit components

DAX futures market, 30-minutes-data, 1997-2000

	Number of models	Mean of gross rate of return	Mean for each class of models					
			Profitable positions			Unprofitable positions		
			Number	Return per day	Duration in days	Number	Return per day	Duration in days
Moving average models								
Cluster 1	45	34.2	299.4	1.18	0.7	500.4	–1.56	0.3
Cluster 2	405	29.5	162.3	0.86	1.3	268.4	–1.27	0.4
Cluster 3	1,674	22.1	83.1	0.63	2.6	122.3	–0.91	0.9
Total	2,124	23.7	102.8	0.68	2.3	158.2	–0.99	0.8
Momentum models								
Cluster 1	38	27.0	357.8	1.21	0.6	540.2	–1.67	0.2
Cluster 2	127	30.9	170.4	0.71	1.4	278.7	–1.15	0.4
Cluster 3	63	22.6	92.4	0.53	2.6	163.9	–0.89	0.7
Total	228	28.0	180.1	0.74	1.6	290.6	–1.17	0.5
Relative strength models								
Cluster 1	49	22.0	389.6	1.23	0.5	570.4	–1.75	0.2
Cluster 2	102	20.0	179.6	0.95	1.0	268.6	–1.24	0.4
Cluster 3	77	-0.2	89.2	0.74	1.7	162.6	–0.89	0.8
Total	228	13.6	194.2	0.94	1.1	297.7	–1.23	0.5
All models								
Cluster 1	132	27.6	349.7	1.21	0.6	537.8	–1.66	0.2
Cluster 2	634	28.3	166.7	0.84	1.3	270.5	–1.24	0.4
Cluster 3	1,814	21.1	83.7	0.63	2.5	125.5	–0.91	0.9
Total	2,580	23.2	117.7	0.71	2.1	182.2	–1.03	0.8

Table 20b: Frequency and performance of stable and unstable trading models

DAX futures market, 30-minutes-data, 1997-2000

	Number of models		Share of stable models	Stable models[5]			Unstable models[1]		
	Stable	Unstable		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 models									
SG 1	146	208	41.2	29.1	23.2	2.35	24.0	19.1	1.96
SG 2	127	227	35.9	22.2	18.6	2.06	20.5	17.1	1.92
SG 3	150	204	42.4	24.9	19.6	2.63	19.6	15.6	2.03
SG 4	122	232	34.5	36.9	28.7	2.93	16.6	11.1	1.35
SG 5	114	240	32.2	32.5	25.0	2.95	21.1	16.0	1.93
SG 6	103	251	29.1	35.1	26.8	2.95	20.9	15.6	1.79
Total	762	1362	35.9	29.7	23.4	2.62	20.4	15.7	1.82
Momentum models									
SG 1	24	14	63.2	28.4	18.8	2.27	29.9	22.5	2.40
SG 2	21	17	55.3	23.5	17.0	2.02	28.0	22.7	2.35
SG 3	24	14	63.2	24.9	16.3	2.26	30.0	22.0	2.68
SG 4	27	11	71.1	29.8	18.4	2.41	26.6	13.0	2.14
SG 5	28	10	73.7	29.1	18.6	2.50	28.2	17.9	2.42
SG 6	25	13	65.8	28.4	17.6	2.36	29.9	17.5	2.49
Total	149	79	65.4	27.5	17.8	2.32	28.8	19.7	2.42
Relative strength models									
SG 4	14	62	18.4	24.2	7.4	1.85	4.7	-3.9	0.35
SG 5	24	52	31.6	29.6	15.4	2.84	13.4	6.1	1.42
SG 6	28	48	36.8	22.2	10.1	1.90	9.1	0.2	0.78
Total	66	162	28.9	25.3	11.4	2.23	8.8	0.5	0.82
All models									
SG 1	170	222	43.4	29.0	22.6	2.34	24.4	19.3	1.98
SG 2	148	244	37.8	22.4	18.3	2.05	21.0	17.5	1.95
SG 3	174	218	44.4	24.9	19.1	2.58	20.2	16.0	2.07
SG 4	163	305	34.8	34.6	25.2	2.75	14.5	8.1	1.17
SG 5	166	302	35.5	31.5	22.6	2.86	20.0	14.4	1.86
SG 6	156	312	33.3	31.7	22.3	2.67	19.4	13.3	1.67
Total	977	1,603	37.9	29.1	21.7	2.55	19.6	14.4	1.75

[5]) Stable models are profitable (GRR > 0) in each of the 4 subperiods, all others are unstable.

Table 21b: Frequency and performance of stable and unstable trading systems

DAX futures market, 30-minutes-data, 1997-2000

t-statistic of the mean of the single returns	Number of models		Share of stable models	Stable models[6])		Unstable models[1])	
	Stable	Unstable		Gross rate of return	Net rate of return	Gross rate of return	Net rate of return
Short-term models (cluster 1)							
<0	–	1	–	–	–	−6.1	−24.4
0-<1	2	9	18.2	10.1	− 9.2	8.6	− 8.0
1-<2	23	17	57.5	20.3	0.3	18.4	1.8
2-<3.0	42	8	84.0	30.1	12.2	28.8	10.9
>3	30	–	100.0	42.5	25.6	–	–
Total	97	35	73.5	31.2	13.1	17.6	0.6
Medium-term models (cluster 2)							
<0	2	19	9.5	−6.4	−13.7	−2.8	−11.9
0-<1	4	70	5.4	8.4	0.5	6.4	− 2.4
1-<2	70	64	52.2	20.5	12.1	16.1	7.4
2-<3.0	119	58	67.2	29.4	21.0	29.5	21.3
>3	138	90	60.5	43.9	34.1	41.9	33.2
Total	333	301	52.5	33.0	24.1	23.0	14.3
Long-term models (cluster 3)							
<0	5	34	12.8	−3.3	− 8.8	−8.6	−13.4
0-<1	4	227	1.7	6.1	1.6	7.8	4.0
1-<2	208	549	27.5	18.6	14.9	15.7	11.9
2-<3.0	190	326	36.8	25.8	21.2	27.7	23.1
>3	140	131	51.7	39.9	34.5	37.1	32.2
Total	547	1,267	30.2	26.3	21.8	18.9	14.8
All models							
<0	7	54	11.5	−4.2	−10.2	−6.5	−13.0
0-<1	10	306	3.2	7.8	− 1.0	7.5	2.2
1-<2	301	630	32.3	19.2	13.2	15.8	11.1
2-<3.0	351	392	47.2	27.5	20.0	28.0	22.6
>3	308	221	58.2	41.9	33.5	39.1	32.6
Total	977	1,603	37.9	29.1	21.7	19.6	14.4

[6]) Stable models are profitable (GRR > 0) in each of the 4 subperiods, all others are unstable.

Table 22b: Performance of 2580 technical trading systems by types of models and subperiods

DAX futures market, 30-minutes-data, 1997-2000

	Number of models		Share of profitable models in %	Gross rate of return	t-statistic	Net rate of return	Duration of profitable positions
	Profitable	Total					
1997							
Moving average models	2,030	2,124	95.6	37.3	1.84	32.6	2.5
Momentum models	226	228	99.1	35.4	1.63	27.0	1.8
Relative strength models	199	228	87.3	20.3	0.98	10.8	1.1
Total	2,455	2,580	95.2	35.7	1.75	30.2	2.3
1998							
Moving average models	2,075	2,124	97.7	37.6	1.36	32.6	2.5
Momentum models	209	228	91.7	34.8	1.21	25.9	1.7
Relative strength models	180	228	78.9	23.4	0.88	13.9	1.1
Total	2,464	2,580	95.5	36.1	1.31	30.4	2.3
1999							
Moving average models	968	2,124	45.6	– 1.7	–0.07	– 7.2	2.3
Momentum models	173	228	75.9	11.0	0.48	1.1	1.5
Relative strength models	95	228	41.7	– 2.3	–0.12	–11.9	1.2
Total	1,236	2,580	47.9	– 0.6	–0.03	– 6.8	2.1
2000							
Moving average models	1,777	2,124	83.7	18.7	0.88	12.6	2.0
Momentum models	222	228	97.4	28.3	1.25	17.3	1.4
Relative strength models	151	228	66.2	12.6	0.58	1.3	1.1
Total	2,150	2,580	83.3	19.0	0.89	12.0	1.8

Table 23b: Performance of 2,580 technical trading systems by types of models and subperiods

DAX futures market, 30-minutes-data, 1997-2000

	Number of models		Share of profitable models	Gross rate of return in %	t-statistic	Net rate of return	Duration of profitable positions
	Profitable	Total					
1997							
SG 1	389	392	99.2	42.9	1.87	37.9	3.1
SG 2	392	392	100.0	41.0	2.05	37.8	3.2
SG 3	384	392	98.0	35.5	2.04	31.1	1.9
SG 4	412	468	88.0	28.0	1.23	21.1	2.0
SG 5	447	468	95.5	34.8	1.79	28.6	1.8
SG 6	431	468	92.1	33.8	1.60	27.2	1.9
Total	2,455	2,580	95.2	35.7	1.75	30.2	2.3
1998							
SG 1	387	392	98.7	37.3	1.26	32.1	3.0
SG 2	368	392	93.9	28.1	1.06	24.4	3.1
SG 3	384	392	98.0	32.4	1.32	27.6	2.1
SG 4	426	468	91.0	39.5	1.32	32.4	2.0
SG 5	453	468	96.8	38.3	1.44	31.9	1.9
SG 6	446	468	95.3	39.3	1.39	32.5	1.9
Total	2,464	2,580	95.5	36.1	1.31	30.4	2.3
1999							
SG 1	185	392	47.2	−3.5	–0.15	−9.5	2.8
SG 2	176	392	44.9	−2.8	–0.15	−6.7	2.9
SG 3	204	392	52.0	1.5	0.10	−3.6	1.8
SG 4	232	468	49.6	1.0	0.04	−6.5	1.9
SG 5	225	468	48.1	−0.1	–0.01	−7.1	1.7
SG 6	214	468	45.7	−0.1	–0.01	−7.5	1.8
Total	1,236	2,580	47.9	−0.6	–0.03	−6.8	2.1
2000							
SG 1	372	392	94.9	26.0	1.13	19.4	2.4
SG 2	340	392	86.7	16.7	0.83	12.5	2.7
SG 3	348	392	88.8	17.0	0.94	11.3	1.6
SG 4	343	468	73.3	15.4	0.64	6.8	1.6
SG 5	387	468	82.7	20.9	1.00	13.0	1.4
SG 6	360	468	76.9	18.6	0.83	10.2	1.5
Total	2,150	2,580	83.3	19.0	0.89	12.0	1.8

Table 24b: Performance of the 25 most profitable trading systems by subperiods

In sample and out of sample
DAX futures market, 30-minutes-data, 1997-2000

	Number	Gross rate of return	t-statistic	Net rate of return	Duration of profitable positions	Number	Gross rate of return	t-statistic	Net rate of return	Duration of profitable positions
			In sample					Out of sample		
1997										
Short	1	81.3	3.13	68.80	0.9					
Medium	5	77.4	3.13	70.04	1.6					
Long	19	78.7	3.18	74.05	2.1					
Total	25	78.6	3.17	73.04	2.0					
1998										
Short	-	-	-	-	-	1	95.5	3.07	83.0	0.9
Medium	14	106.7	3.53	96.93	1.2	5	65.8	2.16	58.1	1.6
Long	11	97.3	3.22	92.48	2.1	19	50.8	1.69	45.9	2.1
Total	25	102.5	3.39	94.97	1.6	25	55.6	1.84	49.8	2.0
1999										
Short	-	-	-	-	-	-	-	-	-	-
Medium	17	50.4	2.16	42.11	1.1	14	1.5	0.05	–10.2	1.0
Long	8	48.5	2.06	42.82	1.5	11	–16.6	–0.78	–22.0	1.9
Total	25	49.8	2.13	42.34	1.2	25	– 6.4	–0.31	–15.4	1.4
2000										
Short	4	68.5	2.76	52.00	0.7	-	-	-	-	-
Medium	11	62.3	2.66	49.48	1.0	17	14.3	0.58	4.5	0.9
Long	10	57.5	2.47	50.77	1.8	8	25.4	1.01	18.9	1.3
Total	25	61.4	2.60	50.40	1.3	25	17.9	0.72	9.1	1.0

Table 25b: Distribution of trading systems by the rate of return and the ratio of profit components over three subperiods

DAX futures market, 30-minutes-data, 1998-2000

	Gross rate of return	Standard deviation	t-statistic
		All models (N = 7740)	
Gross rate of return	18.2	25.4	
Net rate of return	11.8	24.8	
NPP/NPL	0.64	0.14	
DRP/DRL	0.67	0.15	
DPP/DPL	2.91	0.97	
		The 25 most profitable models in sample (N = 75)	
Gross rate of return	71.2	23.9	19.1
Net rate of return	62.6	24.2	18.1
NPP/NPL	0.84	0.21	8.2
DRP/DRL	0.83	0.16	8.6
DPP/DPL	2.54	1.04	– 3.1
		The 25 most profitable models out of sample (N = 75)	
Gross rate of return	22.3	30.3	1.2
Net rate of return	14.5	31.0	0.7
NPP/NPL	0.72	0.14	4.9
DRP/DRL	0.79	0.14	7.4
DPP/DPL	2.22	0.78	– 7.6

Table 26b: Distribution of time by positions and transactions of 2,580 technical trading systems

DAX futures trading based on 30-minutes-data

Net position index	Share in total Sample period in %	Mean of the net position index	Aggregate positions Distribution by type of position		
			Long	Short	Neutral
> 70	26.12	86.24	90.02	–3.78	6.20
50 - 70	9.97	60.41	72.16	–11.75	16.09
30 - 50	7.92	40.14	58.92	–18.78	22.30
10 - 30	7.70	20.02	46.68	–26.67	26.65
–10 - 10	6.77	0.34	36.28	–35.93	27.79
–30 - –10	6.52	–19.69	27.02	–46.71	26.28
–50 - –30	6.44	–40.23	18.66	–58.89	22.45
–70 - –50	7.59	–60.18	11.66	–71.84	16.51
< –70	20.98	–87.30	3.42	–90.72	5.85
Total	100.00	6.54	45.99	–39.45	14.56

	Share in total Sample period in %	Mean of the net transaction index	Aggregate transactions Distribution by type of transaction	
			Buy	Sell
> 70	0.05	82.46	82.53	–0.07
50 - 70	0.25	58.34	58.52	–0.18
30 - 50	1.68	36.71	37.13	–0.42
10 - 30	15.54	16.82	18.24	–1.42
–10 - 10	65.19	0.05	4.39	–4.34
–30 - –10	14.92	–16.92	1.37	–18.29
–50 - –30	2.10	–36.33	0.40	–36.74
–70 - –50	0.22	–58.01	0.08	–58.09
< –70	0.03	–77.25	0.08	–77.33
Total	100.00	0.01	6.72	–6.71

Table 27b: Similarity of different types of technical trading systems in holding open positions

DAX futures trading based on 30-minutes-data

	Relative share of models holding the same – long or short – position		
	More than 90% (|PI| > 80)	More than 80% (|PI| > 60)	More than 70% (|PI| > 40)
	Share in total sample period in %		
Types of models			
By stability			
Stable	34.44	52.15	67.27
Unstable	39.10	62.27	75.98
By duration of profitable positions			
Short-term	39.16	56.34	71.29
Medium-term	34.69	56.52	72.51
Long-term	46.69	63.91	77.11
By type of trading strategy			
Trend-following	48.74	66.46	79.35
Contrarian	28.95	51.90	69.30
All models	34.91	56.36	72.17

Table 28b: Aggregate trading signals of 2,580 technical models and stock price movements

DAX futures trading based on 30-minutes-data

Parameters of the conditions for CSP k	i	Time span J of CSP	More than 10% (20%, 40%) of all models change open positions in the same direction within 3 (5, 10) 30-minutes-intervals					
			From short to long positions (condition 1L)			From long to short positions (condition 1S)		
			Number of cases	Mean of CSP_{t+j}	t-statistic	Number of cases	Mean of CSP_{t+j}	t-statistic
20	3	–3	3056	0.571	48.23	3006	–0.517	–52.26
		5	3056	0.040	1.14	3006	–0.025	–2.76
		10	3056	0.128	3.68	3006	–0.048	–3.90
		20	3056	0.151	1.81	3006	0.012	–2.23
		40	3056	0.265	1.87	3006	0.089	–1.81
40	5	–5	2184	0.834	50.83	2158	–0.758	–57.09
		5	2184	0.045	1.37	2158	–0.035	–2.93
		10	2184	0.115	2.74	2158	–0.073	–4.31
		20	2184	0.124	0.87	2158	0.015	–1.86
		40	2184	0.248	1.31	2158	0.081	–1.70
80	10	–10	1329	1.159	47.86	1228	–1.024	–56.37
		5	1329	0.038	0.76	1228	0.016	–0.28
		10	1329	0.106	1.83	1228	0.031	–0.42
		20	1329	0.119	0.58	1228	0.166	1.49
		40	1329	0.200	0.32	1228	0.273	1.27
			More than 90% of all models hold the same type of open position					
			Long positions (condition 2L)			Short positions (condition 2S)		
		5	3339	0.063	2.79	2835	–0.044	–3.32
		10	3339	0.070	1.16	2835	–0.052	–3.32
		20	3339	0.028	–1.99	2835	0.125	0.87
		40	3339	0.066	–2.60	2835	0.225	0.86

The table presents the means of changes over i business days (CSP_{t+j}) under four different conditions.

Condition 1L (S) comprises all situations where more than 10% (20%, 40%) of all trading systems have been moving monotonically from short to long (long to short) positions over the past 3 (5, 10) trading intervals. The moves are restricted to a range of the position index PI_t between 80 and –80.

Condition 2L (S) comprises all situations beyond this range, i.e., where more than 90% of all trading systems hold long (short) positions. More formally these conditions are defined as follows:
Condition 1L (S): $[PI_t - PI_{t-1}] > k\ (< -k) \cap [PI_{t-n} - PI_{t-n-1}] \geq 0 \leq = 0 \cap [-80 \leq PI_t \leq 80]$
k 20, 40, 80
i 3, 5, 10
n .... 0, 1, ... (i – 1)

Condition 2L (S): PI > 80 (< – 80)
$CSP_{t+j} = 100 * [SP_{t+j} - SP_t] / SP_t$ for j 5, 10, 20, 40
$CSP_{t+j} = 100 * [SP_t - SP_{t+j}] / SP_t$ for j .... –5

The t-statistic tests for the significance of the difference between the mean of the conditional exchange rate changes and the unconditional mean over the entire sample, the latter being as follows (S.D. in parentheses):
For j = 3 0.0134 (0.6723)
5 0.0224 (0.8661)
10 0.0448 (1.2239)
20 0.0897 (1.7678)
40 0.1772 (2.4313)

Table 29b: Aggregate trading signals produced by different types of technical models and stock price movements

DAX futures trading based on 30-minutes-data

Types of models	Time span j of CSP_{t+i}	More than 20% of all models change open positions in the same direction within five 30-minutes intervals ($K = 40$, $i = 5$, $-80 \geq PI \leq 80$)					
		From short to long positions (condition 1L)			From long to short positions (condition 1S)		
		Number of cases	Mean of CSP_{t+i}	t-statistic	Number of cases	Mean of CSP_{t+i}	t-statistic
Trend-following	– 5	1990	0.785	43.32	1999	–0.733	–50.03
	10	1990	0.129	3.03	1999	–0.040	–3.02
	20	1990	0.150	1.42	1999	0.058	–0.76
Contrarian	– 5	2359	0.827	52.83	2269	–0.716	–56.17
	10	2359	0.122	3.11	2269	–0.074	–4.41
	20	2359	0.140	1.34	2269	0.009	–2.07
Short-term	– 5	2270	0.207	16.97	2347	–0.158	–18.65
	10	2270	0.078	1.20	2347	0.074	1.07
	20	2270	0.129	1.00	2347	0.034	–1.46
Medium-term	– 5	2221	0.661	46.82	2134	–0.560	–53.08
	10	2221	0.119	2.76	2134	–0.054	–3.49
	20	2221	0.147	1.41	2134	–0.017	–2.65
Long-term	– 5	2206	0.671	38.20	2137	–0.622	–41.53
	10	2206	0.094	1.86	2137	–0.038	–3.07
	20	2206	0.122	0.80	2137	0.044	–1.14
		More than 90% of alll models hold the same type of open position					
		Long positions (condition 2L: $PI > 80$)			Short positions (condition 2S: $PI < -80$)		
		Number of cases	Mean of CSP_{t+i}	t-statistic	Number of cases	Mean of CSP_{t+i}	t-statistic
Trend-following	10	4950	0.058	0.71	3675	–0.015	–2.35
	20	4950	0.047	–1.63	3675	0.127	1.02
Contrarian	10	2605	0.080	1.44	2525	–0.078	–3.99
	20	2605	0.019	–1.98	2525	0.096	0.15
Short-term	10	3665	0.120	3.76	3259	–0.112	–6.22
	20	3665	0.127	1.22	3259	0.016	–2.02
Medium-term	10	3272	0.101	2.69	2870	–0.095	–5.03
	20	3272	0.046	–1.37	2870	0.078	–0.29
Long-term	10	4532	0.041	–0.20	3740	0.004	–1.60
	20	4532	0.044	–1.65	3740	0.147	1.60

For a definition of the conditions 1L (S) and for the conditions 2L (S) see Table 28b.

The t-statistic tests for the significance of the difference between the mean of the conditional exchange rate changes and the unconditional mean over the entire sample, the latter being as follows (S.D. in parentheses):
For j = 50.0224 (0.8661)
100.0448 (1.2239)
200.0897 (1.7678)

Table 30b: Eight phases of technical trading and stock price movements
All models

DAX futures trading based on 30-minutes-data

Conditions for CSP_{t+j} (= Phaes of technical trading)	Time span j of CSP_{t+j}	(Increasing) Long positions (conditions .L.)			(Increasing) Short positions (conditions .S.)		
		Number of cases	Mean of CSP_{t+j}	t-statistics	Number of cases	Mean of CSP_{t+j}	t-statistics
1A	– 5	565	0.797	26.46	1483	–0.798	–48.61
	5	656	0.094	2.22	1483	–0.037	–2.66
1B	– 5	1619	0.847	45.40	675	–0.673	–37.86
	5	1619	0.028	0.30	675	–0.030	–1.45
2A	5	2606	0.081	3.77	2187	–0.084	–5.36
2B	5	733	–0.001	–0.73	648	0.092	1.32
1A	10	565	0.131	1.84	1483	–0.065	–3.48
1B	10	1619	0.110	2.20	675	–0.092	–2.72
2A	10	2606	0.098	2.23	2187	–0.103	–4.90
2B	10	733	–0.032	–1.81	648	0.123	1.10
1A	20	565	0.108	0.24	1483	0.020	–1.47
1B	20	1619	0.130	0.90	675	0.003	–1.21
2A	20	2606	0.079	–0.30	2187	0.071	–0.42
2B	20	733	–0.156	–3.96	648	0.309	2.58
1A	40	565	0.241	0.59	1483	0.092	–1.28
1B	40	1619	0.251	1.22	675	0.056	–1.20
2A	40	2606	0.099	–1.64	2187	0.197	0.33
2B	40	733	–0.049	–2.84	648	0.320	1.13

Each of the four phases of technical trading defined by the conditions 1L (S) and the conditions 2L (S) for k = 40 and i = 5 (see Table 28b) is divided into two subphases by the conditions A and B:

Condition 1L (S): More than 20% of all trading systems have been moving from short to long (long to short) positions over the past five 30-minutes-intervals within the range $\{-80 \leq PI_t \leq 80\}$ and ....

Condition 1L (S) A: Less than 50% of the models hold long (short) positions, i.e., $PI_t \leq 0$ ($PI_t \geq 0$).

Condition 1L (S) B: More than 50% of the models holg long (short) positions, i.e., $PI_t \geq 0$ ($PI_t \leq 0$).

Condition 2L (S): More than 90% of all trading systems hold long (short) positions, i.e., $PI_t > 80$ ($PI_t < -80$).

Condition 2L (S) A: Comprises the first five 30-minutes-intervals for which condition 2L (S) holds true.

Condition 2L (S) B: Comprises the other 30-minutes-intervals for which condition 2L (S) holds true.

The t-statistics tests for the significance of the difference between the mean of the conditional stock price changes and the unconditional mean over the entire sample, the latter being als follows (S.D. in parentheses):

For j = 5 0.0224 (0.8661)
10 0.0448 (1.2239)
20 0.0897 (1.7678)
40 0.1772 (2.4313)

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