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ÖSTERREICHISCHES INSTITUT FÜR WIRTSCHAFTSFORSCHUNG

TECHNICAL ANALYSIS AND EXCHANGE RATE DYNAMICS

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1. Introduction

Over the past 15 years an increasing number of studies have investigated the expectations formation and trading behavior of foreign exchange dealers (see, e.g., Group of Thirty, 1985; Goodhart-Figliuoli, 1991; Goodhart-Giugale, 1993; Taylor-Allen, 1992; Menkoff, 1995 and 1998; Wolgast, 1997; Lyons, 1998; Lui-Mole, 1998; Cheung-Chinn-Marsh, 1999; Cheung-Chinn, 1999A and B, Cheung-Wong, 2000). The main results of these studies can be summarized as follows:

- The greatest part of market activity is carried out between banks, securities and brokerage houses, commodities firms and industrial corporations. Roughly one third of the trading volume of banks (by far the most important type of market agent) is related to customer orders.
- Most transactions in the foreign exchange market, therefore, are speculative, aimed at making profits from expected exchange rate changes over the very short-run, such as minutes, hours or days.
- Daily turnover in the global foreign exchange market has risen dramatically from \$600 billion in April 1989 to \$1.5 billion in April 2000. Out of all currency pairs, trading volume is by far greatest in the DM/dollar and the yen/dollar market (BIS, 1999, Tables A-1 and B-4).
- Most FX activity is carried out in intraday trading (where a trader closes his open positions at the end of the day). The frequency of switching between long and short positions is extremely high (Lyons, 1998, reports a half live of open positions of 10 minutes).
- Overnight positions are held for several days or even weeks in order to profit from (expected) medium-term price trends. Even though opening and closing these strategic positions contribute little to market turnover, they can influence exchange rate movements since more money is put in overnight positions as compared to intraday positions (according to Wolgast, 1997, the former amount to 10-20 million \$, the latter to 50-150 million \$). The price effect of holding strategic

positions will be the more pronounced the more they are concentrated on one side of the market (long or short).

- Even though the major part of trading activity is carried out on a intraday basis, most dealers consider intraday market trends as unpredictable. Exchange rate movements over the medium run (up to 6 months) are seen as rather unpredictable by roughly 30% of traders, however, an approximately equal share of traders consider medium-term trends as (at least partly) predictable.

- The most important methods of expectations formation and trading are based on the interpretation of news concerning market fundamentals (like interest rates, inflation, current account, etc.) and on technical analysis (both, qualitative approaches like the interpretation of price charts as well as quantitative approaches like the use of moving average and momentum models).

- Most traders do not view technical and fundamental analysis as mutually exclusive. However, they attach to technical analysis relatively more weight at shorter time horizons of expectations and trading (from intraday up to several weeks), and to fundamental analysis relatively more weight at longer horizons.

- Moving average and momentum models are the most widely used quantitative methods of technical analysis.

The results of these investigations into the microstructure of the foreign exchange market, as well as the dollar fluctuations during the 1980s and the poor performance of structural exchange rate models, have increased the interest in theoretical and empirical analysis of the role of non-fundamentalist traders in financial markets. (This interest was also fostered by the stock market boom since the early 1980s).

On theoretical grounds, this interest led to the development of the noise trader approach. The respective models analyze the consequences of the interaction between rational/fundamentalist traders and non-rational/feedback traders for expectations formation, risk, and price overshooting in asset markets (Cutler-Poterba-Summers, 1991; De Long-Shleifer-Summers-Waldmann, 1990A and B; Frankel-Froot, 1990).

On empirical grounds, an increasing number of studies analyzed the performance of trading strategies based on technical analysis in the foreign exchange market and the stock market.

Early studies on the profitability of trading rules in financial markets dealt with the so-called filter rules, which generate a buy signal when the price exceeds the most recent low by X% and a sell signal when it falls below the most recent high by Y%. The main purpose of these studies was to test for market efficiency in its weak form (Alexander, 1964; Poole, 1967; Logue-Sweeney, 1977; Cornell-Dietrich, 1978; Dooley-Shafer, 1983; Sweeney, 1986). Even though the studies detected an excessive ex-post-profitability of filter rules in most cases they contributed little to a better understanding of actual trading behavior since filter rules are not considered a component of technical analysis in either theory or practice (Kaufman, 1987, does not even mention it).[1])

The next generation of studies on the performance of trading rules analyzed the ex-post profitability of those rules which are actually used in practice. Most studies focused on the performance of quantitative technical models (moving average and momentum models) in the foreign exchange market (Schulmeister, 1987, 1988; Levich-Thomas, 1993; Menkhoff-Schlumberger, 1995) as well as in the stock market (Goldberg-Schulmeister, 1988; Schulmeister-Goldberg, 1989; Brock-Lakonishok-LeBaron, 1992). In addition, some studies tested the profitability of those technical trading rules which are based on certain configurations of price movements (Chang-Osler, 1999; Osler, 2000; Lo-Mamaysky-Wang, 2000). These configurations like head-and-shoulders or top and bottom formations were identified with the help of computer software similar to that developed for fingerprint identification.

All of these studies found technical trading systems to be "abnormally" profitable. 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

[1]) The main reason why filter rules are not used in practice stems from the fact that their profitability is much more sensitive to parameter changes than the profitability of, e.g., moving average and momentum models (see Schulmeister, 1987, for the performance of filter rules as compared to "true" models of technical analysis).

post profitable trading rules which a trader in practice would not be able to choose ex ante (this possible selection bias concerns, however, only the tests of quantitative technical models). 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).

The third generation of studies on trading rules focused on their (possible) profitability ex ante and consequently on the problem of model selection. One approach applies the logic of genetics to this problem: the variation and combination of the parameters of the models as well as their selection and application are continuously replicated (Neely-Weller-Dittmar, 1997; Neely-Weller, 1999; Fyfe-Marney-Tarbert, 1999). Even though this "genetic programming" approach might enable one to find profitable models ex ante for currency trading, it contributes little to a better understanding of model selection in practice since the "genetic" algorithm as well as the trading models themselves (they do not belong to technical analysis) are the constructions of researchers. The same is true of model selection based on the analytic of neural networks (Gencay-Stengos, 1997 and 1998; Gencay, 1999; Fernandez-Rodriguez - Gonzalez-Martel – Sosvilla-Rivero, 2000).

What is missing from all of this work is a simulation of those kinds of model selection (out of a great number of models) which are actually adopted in practice together with a test of the ex-ante-profitability of the selected technical models.

Another problem that has not yet been sufficiently explored concerns the causes of the profitability of technical trading systems (even if they are profitable only ex post). In particular, it remains unclear which types of non-randomness in the dynamics of speculative prices contribute most to technical trading being profitable.

Finally, the feed-back of the use of a great variety of technical trading systems on the dynamics of speculative prices has not yet been analyzed empirically. This concerns in particular the relationship between the share of models opening and/or holding the same - long or short - position and the subsequent price movements.

2. Scope and structure of the study

The purpose of this study is two fold. First, the study documents the profitability of a wide range of technical trading rules and then carefully examines the factors responsible for this profitability. Second, this study explores the relationship between the use of technical trading systems in the foreign exchange market and exchange rate dynamics. The specific objectives of this study are as follows:

- Provide an analysis of the ex-post-profitability of a great number of those technical trading systems which are actually used in practice (moving average and momentum models). Special attention shall be given to the components of the profitability of technical currency trading and how they are related to the pattern of exchange rate movements.

- Provide a simulation of the process of model selection based on their performance in the past and analysis of 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 the best over a certain "test period" in the past, and if he then follows these models over the subsequent period, would he 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 exchange rate 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 currency trading and exchange rate dynamics in detail, the study is restricted to the two most active currency markets, the deutschemark/dollar and the yen/dollar market. The analysis makes use of daily exchange rates for these two currency pairs (mid rates at noon in New York as published by the Federal Reserve Bank of New York[2]).

The study covers the period from January 1973 to December 1999 in the case of the DM/dollar market[3]) and from January 1976 to December 1999 in the case of the yen/dollar market (the latter was not fully liberalized until the end of 1975, as the Bank of Japan succeeded in pegging the yen to the dollar over certain subperiods between 1973 and 1975).

The structure of the study is as follows.

In section 3 the ex-post-profitability of 948 moving average models and 76 momentum models is tested for the whole sample period. The study then examines those properties of exchange rate movements are elaborated which cause technical trading systems to be profitable.

Section 4 explores the ex-ante-profitability of technical trading in the following manner. The period under investigation is divided in several subperiods; then the profitability of those models which perform best over the period is tested over subsequent period.

Section 5 investigates the impact of the use of many different trading models upon exchange rate movements. An index of the aggregate transactions and open positions of the 1024 technical models is calculated at every point in time (day). 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 exchange rate movements is analyzed.

Section 6 evaluates the results of the study in the context of long-lasting controversies in economics. This concerns in particular the issue of stabilizing versus destabilizing and of profitable versus unprofitable speculation, the process of (rational) expectations formation, and the issue of market efficiency.

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[2]) The exchange rate series is downloaded from: http://www.federalreserve.gov/releases/H10/hist/

[3]) The fact that in 1999 DM/dollar trading was substituted by Euro/dollar trading does not affect the results of the simulations given the fixed DM/Euro exchange rate.

3. The performance of technical trading systems over the whole sample period

3.1 How moving average models and momentum models 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, and Pring,1985).

The qualitative approaches rely on the interpretation of some (purportedly) typical configurations of the ups and downs of price movements like head and shoulders or top and bottom formations. 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 and momentum models.

The first type of model consists of a (unweighted) short-term moving average (MAS) and an long-term moving average (MAL) of past prices. The length of MAS usually varies between 1 day (in this case the original price series serves as the shortest possible MAS) and 8 days, that of MAL between 10 and 30 days.

The trading rule of the basic version of moving average models is as follows:

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: Hold a long position when the difference MAS-MAL is positive, otherwise hold a short position.

The second type of model works with the difference between the current price and that i days ago:

$M(i) = P_t - P_{t-i}$

The trading rule of the basic version of momentum models is as follows:

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

Since the variables (MAS-MAL) or M(i) fluctuate around zero, they are often called "oscillators".

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 the rule to hold a neutral position as long as the moving average or momentum oscillator remains within this band (however, also other trading rules can be assigned to crossovers of the upper and lower bound). In the case of MA models one can operate with weighted instead of unweighted moving averages. More sophisticated momentum models use also the second difference of prices, and so on.

This study restricts itself to the analysis of only the basic version of moving average and momentum models in order to avoid the suspicion of "model mining" (the number of modified models becomes easily very great through the variation and combination of the additional parameters).

Short-term price oscillations often cause technical models to produce "wrong" signals. In order to filter them out the signal execution is often delayed by n days according to the following rule: Execute a signal only if it remains valid over n consecutive days. In this study only the shortest possible lag of signal execution is tested (1 day).

Figure 1a and tables 1a and 2a demonstrate how moving average model (MAS=1, MAL=16) and a momentum model (time span i = 8) performed in the DM/dollar market over the year 1992 (this year was chosen since the exchange rate level in the DM/dollar as well as in the yen/dollar market was roughly the same at the beginning and the end of the year).[4])

On January 2, both models signaled a short position and hence $1 is sold for 1.5283 DM (it is assumed that the amount of the open position is always $1. Due to a rise in the exchange rate, both models went long the next day, suffering a loss of 1.21 cents ([1.5283-1.5470]/1.5470). Since this price movement did not continue but reversed its direction both models had to go short on January 6, and 7, respectively, again suffering a significant loss of almost 2 cents. The moving average model successfully exploited the two strong appreciation taking place between January 8, and March 16, so that its overall performance became profitable for the first time (the annualized rate of return from all trades amounted to 11.4% by March 17, - table 1a).

The momentum model performed worse since it produced unprofitable signals in reaction to the countermovements which occurred during the two dollar appreciation. The higher sensitivity of the momentum model to price changes as compared to the moving average model can also be seen from the fact that the momentum oscillator crosses the zero line more frequently than the MA oscillator (figure 1a). For this reason the momentum model produced many - mostly unprofitable - trading signals between mid of March and end of April when the exchange rate fluctuated around a fairly stable level ("whipsaws"). However, all losses were relatively small because the price movements were small. As a consequence the overall rate of return of the momentum model was still highly negative by the end of April.

This observation points to a general problem of technical trading. These strategies can incur substantial losses over periods when prices do not move along strong and persistent upward or downward trends. Consequently, technical traders can "survive" those periods only if they have access to sufficiently large financial resources.

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[4]) The letters "a" and "b" attached to the number of tables or figures refer to the DM/dollar and the yen/dollar exchange rate, respectively. Tables and figures concerning DM/dollar trading are embedded in the maintext, tables and figures concerning yen/dollar trading are collected in a statistical supplement.

Figure 1a: Technical trading signals for the DM/dollar exchange rate 1992

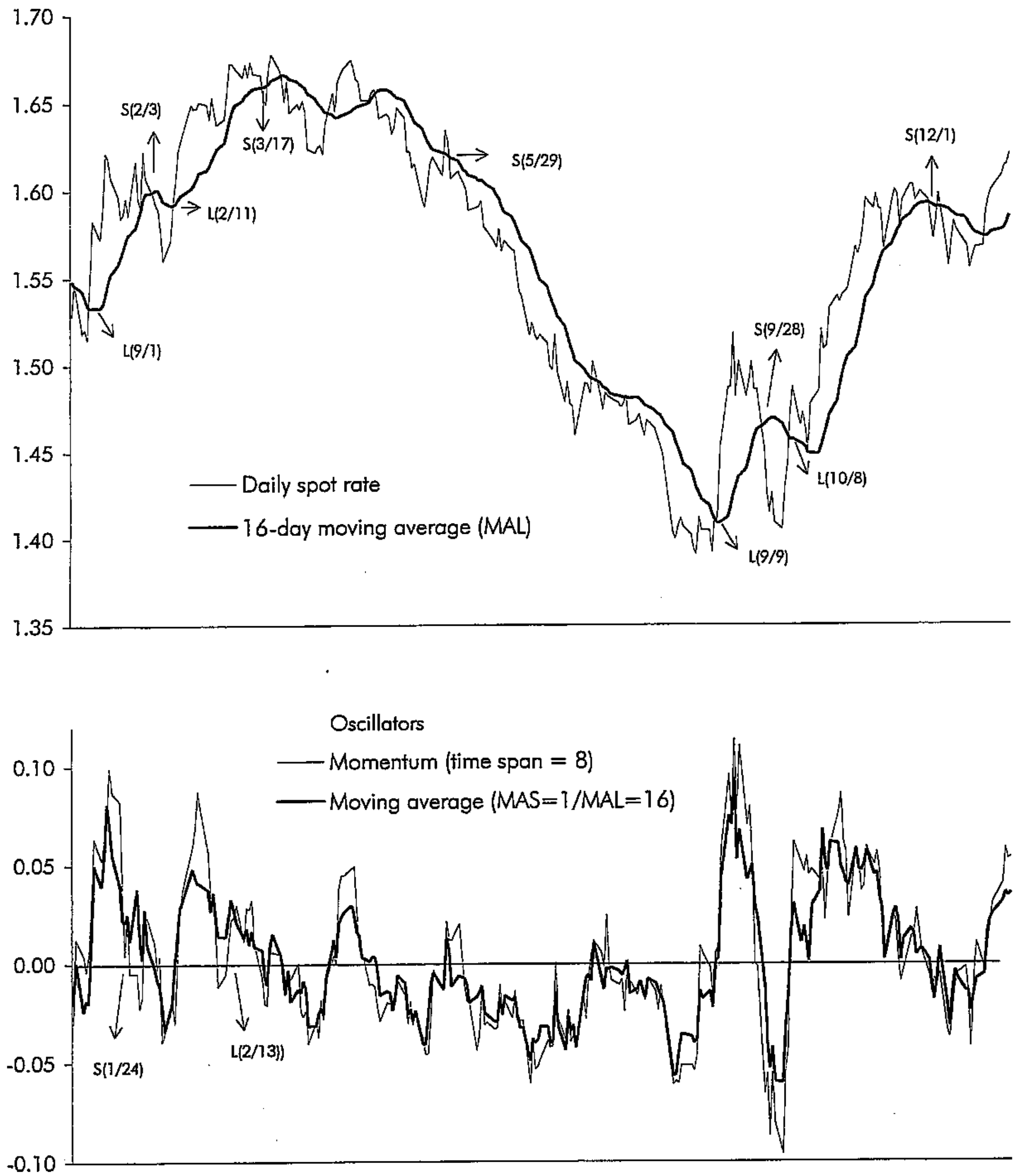

Table 1a: Performance of technical trading systems

Price series: Daily DM/dollar exchange rate
Begin of trading: 01/01/1992
End of trading: 12/31/1992

Signal generating process

Trading System: Moving averages (SG1)
Short-term moving average (MAS): 1
Long-term moving average (MAL): 16

The sequence of long, short and neutral positions

Date	Signal	Duration	Price	Single rate of return	Rate of return per year
01/02/1992	s	0	1.5283	0.00	0.00
01/03/1992	l	1	1.5470	–1.21	–441.21
01/06/1992	s	3	1.5188	–1.86	–279.73
01/09/1992	l	3	1.5465	–1.79	–253.24
02/03/1992	s	25	1.5975	3.19	–18.98
02/11/1992	l	8	1.5920	0.35	–12.03
03/17/1992	s	35	1.6525	3.66	11.40
03/19/1992	l	2	1.6700	–1.05	6.14
03/24/1992	s	5	1.6645	–0.33	4.29
04/13/1992	l	20	1.6552	0.56	5.46
04/30/1992	s	17	1.6525	–0.16	4.18
05/27/1992	l	27	1.6338	1.14	6.27
05/29/1992	s	2	1.6065	–1.70	1.99
07/24/1992	l	56	1.5018	6.97	13.92
07/27/1992	s	3	1.4831	–1.26	11.49
08/06/1992	l	10	1.4820	0.07	11.09
08/07/1992	s	1	1.4650	–1.16	9.10
09/09/1992	l	33	1.4115	3.79	13.41
09/28/1992	s	19	1.4520	2.79	16.24
10/08/1992	l	10	1.4720	–1.36	13.89
12/01/1992	s	54	1.5820	6.95	19.24
12/04/1992	l	3	1.5975	–0.97	18.02
12/07/1992	s	3	1.5682	–1.87	15.85
12/22/1992	l	15	1.5870	–1.18	13.97
12/31/1992	n	9	1.6197	2.02	15.64

The profitability of the trading system

Gross rate of return: 15.60
Transaction costs per trade: 0.02
Net rate of return: 14.64
Number of trading signals: 25
Long: 12
Short: 12
Neutral: 1
Number of transactions: 48
Number of positions:
Long: 12
Short: 12
Average duration of positions: 15.17
Long: 14.67
Short: 15.67
Sum of profits: 31.50
Profitable positions: 11
Average return:
Per position: 2.86
Per day: 0.106
Average duration: 26.91
Sum of losses: 15.90
Unprofitable positions: 13
Average return:
Per position: –1.22
Per day: –0.234
Average duration: 5.23

The strong dollar depreciation between the beginning of May and the end of August, as well as the subsequent appreciation which lasted until the end of November, were successfully exploited by both models. Only four, highly profitable trades were sufficient to render the overall performance of both models over the year 1992 positive. The moving average model produced gross rate of return of 15.6%, the momentum model 12.1% (the gross return is calculated as the sum over all single profits and losses in cents).

The net rate of return (14.6% and 10.5%) is only slightly smaller given the low transactions costs in the competitive foreign exchange market. The calculations operate with (assumed) transaction costs of 0.02% per trade, somewhat less than reported in recent studies (Cheung-Chinn-Marsh, 1999; Cheung-Chinn, 1999A; Goodhart-Figliuoli, 1991)[5]).

For any open position interest is earned from the long position and paid for the short position.[6]) Thus, the overall effect can be roughly estimated by comparing the overall duration of the long and the short dollar positions (given the relatively stable interest differential in the short run). Inspection reveals that during the period of our example (1992) interest earnings and interest costs roughly offset each other since the duration of the long and short positions were approximately equal (see tables 1a and 2a).[7])

[5]) The relationship between trading signals, transactions and open positions is as follows. The number of overall transactions is twice the number of trading signals minus 2 since every signal induces two transactions, namely, closing the former position and opening the new one (except for the first and last signal). The number of open positions is therefore half the number of transactions.

[6]) It is therefore assumed in the study that traders do not invest own capital as is usually the case in the interbank market. Consequently, the rate of profit (or loss) relative to own capital invested is theoretically indefinite. If the currency trading were carried out in the futures markets the rates of return to own capital would be roughly ten to twenty times higher than those reported in this study (margin requirements amount to between 5% and 10% of the contract value).

[7]) Actually, the short positions lasted on average by 1.0 (moving average model) and 1.5 days (momentum model) longer than the long positions. At the same time the DM interest rate in the money market was permanently higher in 1992 than the dollar interest rate (on average by 5.9 percentage points). Hence, accounting for this difference would result in a higher profitability of both technical models as compared to

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

GRR = NPP*DRL*DPP – NPL*DRL*DPL

The structure of the overall profitability of the moving average and momentum model is as follows. Both models produce a greater number of single losses than single profits (tables 1a and 2a). Moreover, the average return per day (in absolute terms) during unprofitable positions was roughly twice as high as during profitable positions. The overall profitability is therefore due to the fact that the duration of profitable positions lasts much longer than the unprofitable positions (by a factor of roughly 5 and 4, respectively - tables 1a and 2a).

Figure 1b and table 1b show that the moving average model with MAS=1 and MAL=16 performed much worse in the yen/dollar market than in the DM/dollar market in 1992. Even though the model successfully exploited the main exchange rate trends, it still produced an overall loss of 6.1% due to the signaling of far too many unprofitable positions. This resulted from the fact that the long-term moving average reacted too sluggishly to some steep and strong exchange rate movements (in particular in January and September).

The momentum model with time span i = 16 produced much less trading signals, thereby avoiding many of the single losses incurred by the moving average model. At the same time the momentum model took advantage of the main exchange rate trends so that it was able to produce an overall gross return of 11.2% (table 2b).

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the calculations in table 1a and 2a. The effect of the interest differential on the profitability of currency speculation will be examined in more detail below.

Table 2a: Performance of technical trading systems

Price series: Daily DM/dollar exchange rate
Begin of trading: 01/01/1992
End of trading: 12/31/1992

Signal generating process

Trading System: Momentum (SG1)
Time span i of M: 8

The sequence of long, short and neutral positions

Date	Signal	Duration	Price	Single rate of return	Rate of return per year
01/02/1992	s	0	1.5283	0.00	0.00
01/03/1992	l	1	1.5470	–1.21	–441.21
01/07/1992	s	4	1.5207	–1.73	–214.49
01/08/1992	l	1	1.5152	0.36	–156.66
01/24/1992	s	16	1.5860	4.46	31.34
01/30/1992	l	6	1.6220	–2.22	–4.31
02/04/1992	s	5	1.5925	–1.85	–24.15
02/05/1992	l	1	1.5895	0.19	–21.41
02/06/1992	s	1	1.5770	–0.79	–29.06
02/13/1992	l	7	1.6230	–2.83	–48.85
02/28/1992	s	15	1.6373	0.87	–30.40
03/03/1992	l	4	1.6565	–1.16	–35.34
03/16/1992	s	13	1.6658	0.56	–26.38
03/19/1992	l	3	1.6700	–0.25	–26.55
03/24/1992	s	5	1.6645	–0.33	–26.40
03/30/1992	l	6	1.6493	0.92	–20.78
03/31/1992	s	1	1.6465	–0.17	–21.24
04/13/1992	l	13	1.6552	–0.53	–20.41
04/14/1992	s	1	1.6451	–0.61	–22.39
04/15/1992	l	1	1.6618	–1.00	–25.70
04/27/1992	s	12	1.6510	–0.65	–25.10
05/27/1992	l	30	1.6338	1.05	–17.31
06/03/1992	s	7	1.6044	–1.83	–20.89
07/09/1992	l	36	1.5175	5.73	–5.85
07/10/1992	s	1	1.4958	–1.45	–8.61
07/23/1992	l	13	1.4835	0.83	–6.57
07/28/1992	s	5	1.4740	–0.64	–7.54
07/29/1992	l	1	1.4837	–0.65	–8.65
07/30/1992	s	1	1.4818	–0.13	–8.83
09/03/1992	l	35	1.4120	4.94	–0.20
09/07/1992	s	4	1.4041	–0.56	–1.02
09/09/1992	l	2	1.4115	–0.52	–1.78
09/24/1992	s	15	1.4855	4.98	5.16
10/08/1992	l	14	1.4720	0.92	6.10
11/19/1992	s	42	1.5796	6.81	13.02
11/23/1992	l	4	1.6024	–1.42	11.27
11/30/1992	s	7	1.5935	–0.56	10.42
12/18/1992	l	18	1.5665	1.72	11.68
12/21/1992	s	3	1.5672	0.04	11.63
12/22/1992	l	1	1.5870	–1.25	10.31
12/31/1992	n	9	1.6197	2.02	12.08

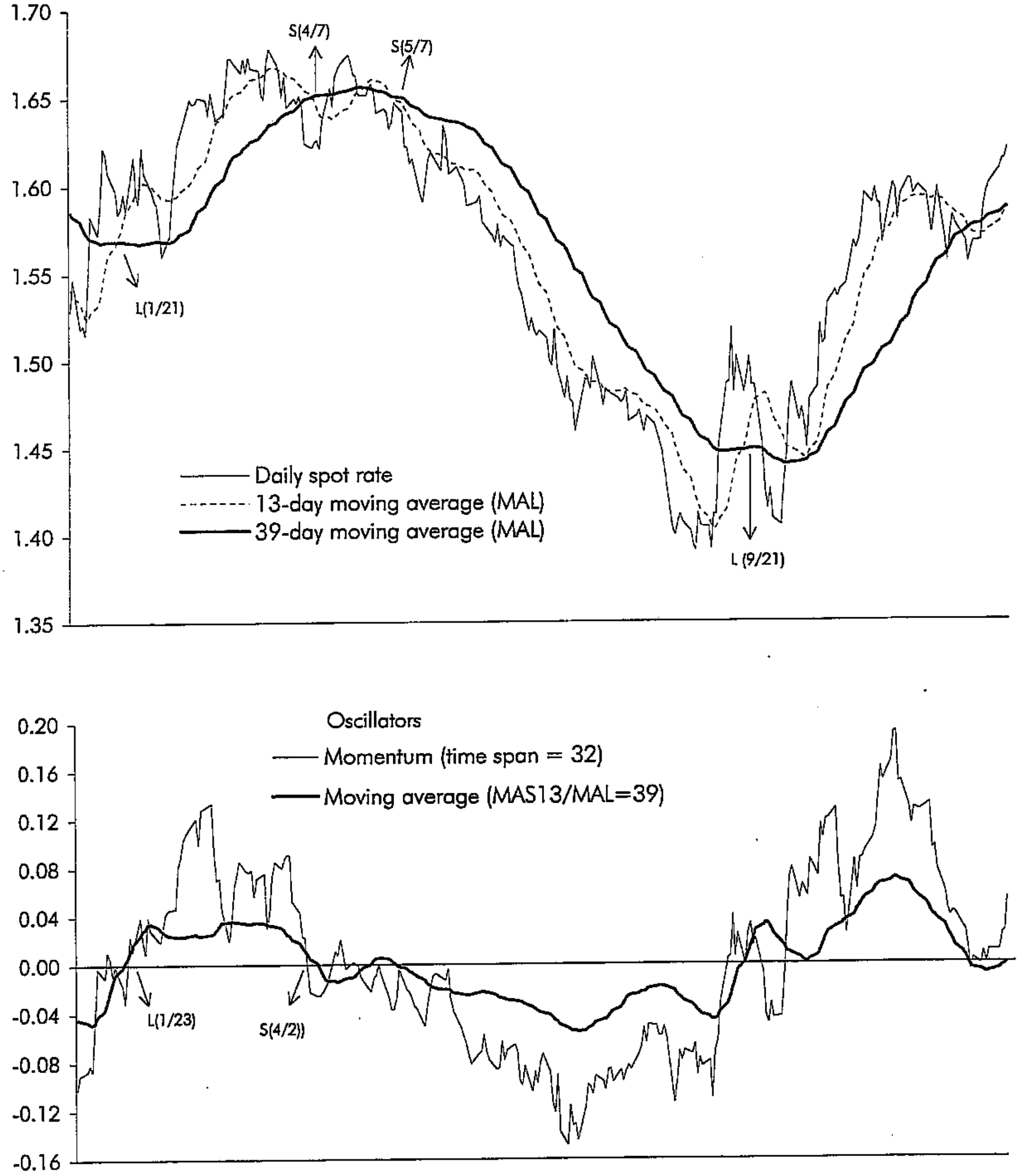
The profitability of the trading system

Gross rate of return: 12.05
Transaction costs per trade: 0.02
Net rate of return: 10.45
Number of trading signals: 41
    Long: 20
    Short: 20
    Neutral: 1
Number of transactions: 80
Number of positions:
    Long: 20
    Short: 20
Average duration of positions: 9.10
    Long: 8.35
    Short: 9.85
Sum of profits: 36.42
Profitable positions: 16
    Average return:
        Per position: 2.28
        Per day: 0.136
    Average duration: 16.69
Sum of losses: –24.37
Unprofitable positions: 24
    Average return:
        Per position: –1.02
        Per day: –0.251
    Average duration: 4.04

Figures 2a and 2b demonstrate how "slow" models performed in 1992 for the DM/dollar and the yen/dollar markets. Due to the relatively long moving averages used in the moving average rules and the relatively long time spans used in the momentum models, only few trading signals were produced as compared to the models shown in figure 1a and 1b. As a consequence, these models successfully exploited the longer term exchange rate trends, however, they missed profit opportunities that shorter but still persistent price movements would have provided. Their overall performance was only moderately profitable with the exception of the momentum model for the case of DM/dollar exchange rate ($i = 32$) which produced an annual rate of return of 18.6% (tables 3a and 3b).

Table 3a and 3b compare the performance of six moving average and six momentum models in the DM/dollar and the yen/dollar markets in 1992. The models were chosen in such a way as to cover wide ranges of long-term moving average lengths and time spans. I have also included one model that operates with a short-term moving average greater than 1 so as to include an extremely "slow" model.

Figure 2a: Technical trading signals for the DM/dollar exchange rate 1992



Several interesting observations can be made from tables 3a and 3b. First, the profitability of technical trading varied remarkably across the 12 tested models, 3 produced an overall loss in the DM/dollar market and 6 in the yen/dollar market. The difference in the gross rate of return between the worst and the best performing models amounted to 26.1 percentage points in DM/dollar trading and to 23.9 percentage points in the yen/dollar trading. Second, the relationship between the duration of profitable positions (DPP) and the profitability of the models is rather loose (given the specific price trends realized in a certain sample period one would expect that the most profitable models display a similar duration of their profitable positions). In the DM/dollar market, e.g., the two best performing models show a similar duration of profitable positions (35.6 days and 26.9 days, respectively), however, the moving average model (1/40) and the momentum model (8) performed not significantly worse even though the duration of their profitable position was rather different (64.3 and 16.7 days, respectively).[8]) Third, the number of profitable positions is always than the number of unprofitable positions. Forth, 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 yen/dollar market displays a very similar trading pattern in spite of the fact that the average profitability is clearly lower than in the DM/dollar market (table 3b). 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.

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[8]) A careful inspection of the profitable signals produced by these four models reveals that the fastest model, i.e., the momentum model 8 which signaled 40 open positions, exploited the relatively short but still persistent price trends successfully, it produced, however, unprofitable signals during long-term price trends due to its higher sensitivity to price changes. The opposite is true for the slowest model, i.e., the moving average model 1/40 (the trading behavior of the two best performing models represents an efficient compromise between these two extremes).

Table 3a: Pattern of DM/dollar-trading 1992

Moving average models

Length i of MAS	1	1	1	1	1	13
Length i of MAL	8	16	24	32	40	39
Lag of signal execution	0	0	0	0	0	0
Gross rate of return	6.58	15.60	–0.16	6.84	13.10	8.40
Sum of profits	37.41	31.50	23.97	24.52	27.62	18.04
Profitable positions						
Number	17	11	5	5	4	3
Average return						
Per position	2.20	2.86	4.79	4.90	6.90	6.01
Per day	0.147	0.106	0.107	0.099	0.107	0.060
Average duration in days	15.00	26.91	44.80	49.40	64.25	100.33
Sum of losses	–30.83	–15.90	–24.13	–17.68	–14.52	–9.64
Unprofitable positions						
Number	30	13	19	15	14	4
Average return						
Per position	–1.03	–1.22	–1.27	–1.18	–1.04	–2.41
Per day	–0.283	–0.234	–0.172	–0.151	–0.136	–0.153
Average duration in days	3.63	5.23	7.37	7.80	7.64	15.75

Momentum models

Time span i	8	16	24	24	32	40
Lag of signal execution	0	0	0	1	0	0
Gross rate of return	12.05	–7.51	–3.98	1.09	18.57	0.77
Sum of profits	36.42	20.50	17.60	16.01	29.20	25.62
Profitable positions						
Number	16	6	12	5	9	7
Average return						
Per position	2.28	3.42	1.47	3.20	3.24	3.66
Per day	0.136	0.094	0.063	0.058	0.091	0.086
Average duration in days	16.69	36.17	23.25	55.60	35.56	42.57
Sum of losses	–24.37	–28.01	–21.58	–14.92	–10.63	–24.85
Unprofitable positions						
Number	24	16	14	7	9	15
Average return						
Per position	–1.02	–1.75	–1.54	–2.13	–1.18	–1.66
Per day	–0.251	–0.191	–0.254	–0.173	–0.242	–0.377
Average duration in days	4.04	9.19	6.07	12.29	4.89	4.40

Tables 3a and 3b also demonstrate how the lag of signal execution by 1 day affects the performance of technical currency trading, taking the momentum model (24) as an example. Since exchange rate movements change their direction rather frequently from day to day, this simple delay filter strongly reduces the number of open positions, namely, from 26 to 12 days in the case of DM/dollar trading and from 18 to 10 days in yen/dollar trading, however, this filter also causes profitable signals to be executed only with a lag of one day. In the case of the momentum model (24) the positive effect of the delay filter (e.g., avoiding unprofitable trades) was greater than its negative effect (e.g., missing profit opportunities) so that the overall gross rate of return increased by 5.1 and 2.3 percentage points in DM/dollar and yen/dollar trading, respectively.

3.2 The profitability of technical trading systems and its components over the entire 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 15 days and a long-term moving average (MAL) between 5 and 40 days are tested (478 models). In the case of momentum models the time span i runs from 3 to 40 days (38 models).

Each model is simulated with and without a lag of signal execution by one day (delay filter). Hence, a total of 1024 different technical trading models are analyzed in this 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 foreign exchange 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 influential study by Brock-Lakonishok-LeBaron, 1992, on technical stock trading) have not been tested because those extremely slow models are not used in practice, at least not in the currency markets.[9])

3.2.1 *Overview of the performance of 1024 trading systems*

Tables 4a and 4b show the performance of six moving average and six momentum models over the entire sample period. The selection comprises models which are very different with respect to their price sensitivity and hence the number of trading signals. The fastest models operating with relatively short moving averages or time spans in the case of

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[9]) In the DM/dollar market the moving average rules (1/150), (5/150), (1/200) and (2/200) would have signaled only 7.2, 3.6, 6.8 and 4.5 open positions per year between 1973 and 1999. This are much less open positions than professional currency trader 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.

momentum models display an average duration of profitable positions between 20 and 30 days respectively (they focus on the exploitation of short-term exchange rate trends like the moving average model 1/16 or the momentum model 9 in the case of DM/dollar trading). Most of the selected models display an average duration of profitable positions between 30 and 60 days, only relatively few specialize on the exploitation of long-term exchange rate trends like the momentum model 30 with the delay filter and the moving average model 11/30 in the case of DM/dollar trading, or the moving average model 8/30 in the case of yen/dollar trading.

All of the selected models are profitable, their gross rates of return center around 10% per year (transaction costs would have reduced gross earnings by less than half a percentage point in almost all cases).[10] There is no clear relationship between the average duration of profitable positions and the overall profitability across the different models. However, in the DM/dollar market short-term and medium term models seem to perform better than long-term models, whereas the opposite prevails in the yen/dollar market.

All selected models have the following trading patterns in common:

- The number of profitable trades is lower than the number of unprofitable trades (except for two moving average models trading in the yen/dollar market).
- The average return per day during profitable positions is smaller (in absolute terms) than during unprofitable positions.
- Profitable positions last on average 3 to 6 times longer than unprofitable positions.

[10] The annual rates of return shown in tables 4a and 4b can also be conceived as excess returns from technical currency speculation over the entire sample period. This is so because the benchmark for excessive profitability is a rate of return of zero (given the assumption that traders do not invest own capital). If one would use the return from buy and hold a long dollar position as benchmark then the annual excess return would be higher by 1.8 percentage points in the case of DM/dollar trading and by 4.5 percentage points in the case of yen/dollar trading (the dollar depreciated vis-a-vis the DM between 1973 and 1999 by 39.4% and vis-a-vis the yen between 1976 and 1999 by 66.5%).

Table 4a: Pattern of DM/dollar-trading 1973/1999

Moving average models

Length i of MAS	1	3	5	11	1	2
Length i of MAL	16	30	21	30	16	31
Lag of signal execution	0	0	0	0	1	1
Gross rate of return per year	11.12	10.10	10.33	8.33	8.50	9.58
Sum of profits per year	23.13	18.05	19.00	14.75	19.64	16.61
Profitable positions						
Number per year	9.07	4.81	5.48	3.41	6.22	4.26
Average return						
Per position	2.55	3.75	3.47	4.33	3.16	3.90
Per day	0.086	0.063	0.071	0.057	0.077	0.060
Average duration in days	29.68	59.49	48.90	75.49	41.07	64.79
Sum of losses per year	–12.01	–7.95	–8.67	–6.42	–11.14	–7.03
Unprofitable positions						
Number per year	19.62	7.22	7.37	4.11	10.48	6.00
Average return						
Per position	–0.61	–1.10	–1.18	–1.56	–1.06	–1.17
Per day	–0.125	–0.101	–0.089	–0.059	–0.102	–0.079
Average duration in days	4.88	10.90	13.18	26.25	10.46	14.86
Single rates of return						
Mean	0.388	0.840	0.804	1.108	0.509	0.934
t-statistic	4.867	4.310	4.458	3.857	3.748	4.219
Median	–0.293	–0.334	–0.215	–0.265	–0.406	–0.258
Standard deviation	2.215	3.507	3.355	4.084	2.882	3.678
Skewness	16.122	2.118	2.133	1.295	2.224	1.921
Excess kurtosis	3.274	5.326	6.639	1.790	7.250	4.225
Sample size	775	325	347	203	451	277

Momentum models

Time span i	9	23	34	9	23	30
Lag of signal execution	0	0	0	1	1	1
Gross rate of return per year	11.53	10.66	7.77	9.20	9.80	7.36
Sum of profits per year	24.82	18.72	15.58	20.88	16.11	14.47
Profitable positions						
Number per year	12.70	7.77	5.22	7.55	4.59	3.67
Average return						
Per position	1.95	2.41	2.99	2.76	3.51	3.95
Per day	0.096	0.066	0.055	0.083	0.059	0.053
Average duration in days	20.38	36.28	54.09	33.42	59.43	74.46
Sum of losses per year	–13.29	–8.06	–7.81	–11.68	–6.32	–7.11
Unprofitable positions						
Number per year	18.96	9.59	7.89	10.92	5.22	5.15
Average return						
Per position	–0.70	–0.84	–0.99	–1.07	–1.21	–1.38
Per day	–0.125	–0.097	–0.095	–0.104	–0.069	–0.077
Average duration in days	5.60	8.65	10.48	10.31	17.66	17.89
Single rates of return						
Mean	0.364	0.614	0.593	0.498	0.999	0.836
t-statistic	5.035	4.591	3.525	4.090	4.487	3.381
Median	–0.167	–0.105	–0.242	–0.268	–0.093	–0.316
Standard deviation	2.114	2.892	3.162	2.717	3.616	3.805
Skewness	3.171	2.801	2.159	2.093	1.961	1.452
Excess kurtosis	17.253	10.072	5.635	7.527	4.870	2.399
Sample size	855	469	354	499	265	238

The overall profitability of the models is therefore due to the exploitation of persistent exchange rate trends. 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 exchange rate fluctuations.

The distribution of the single rates of return reflect the following regularities:

- The median is negative.
- The standard deviation is several times higher than the mean.
- The distribution is skewed to the right and 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 of every model shown in tables 4a and 4b exceeds 3.0 (in many cases it is even higher than 4.0) one can conclude that the probability of making an overall loss by following the trading signals of these models over the entire sample period was less than 0.05% in most cases.[11])

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

[11]) 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 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.

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).[12]

Figures 3a and 3b show the distribution of all 1024 trading systems by their annual gross rates of return over the entire sample period. On average they produce a mean return of 7.9% per year in the case of DM/dollar trading, and of 9.1% in the case of yen/dollar trading, respectively. The standard deviation amounts to 1.39 (DM/dollar) and 1.13 (yen/dollar), respectively. The best performing models produce an annual return of roughly 12%, the worst models roughly 4% (DM/dollar) and 5% (yen/dollar), respectively.

The t-statistic of the mean of the single rates of return exceeds 2.5 in almost all cases (figure 4a and 4b) which implies a probability of making an overall loss by blindly following theses rules of less than 0.5%. 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.

Even though all these observations concern only the ex-post performance of technical trading systems the result of the following thought experiment is still remarkable. If a trader had selected at random one out of these 1024 trading models at the beginning of the sample period and had blindly followed its trading signals over the next 27 (24) years then – with a probability of 0.66 - he would have made an annual gross return between 6.5% and 9.3% (DM/dollar) or between 8.0% and 10.2% (yen/dollar) with little relevant risk of suffering an overall loss (as measured by the t-statistic). The level of risk would have been small even if the trader had by chance selected one of the worst performing models (their t-statistics amount still to roughly 2.0).

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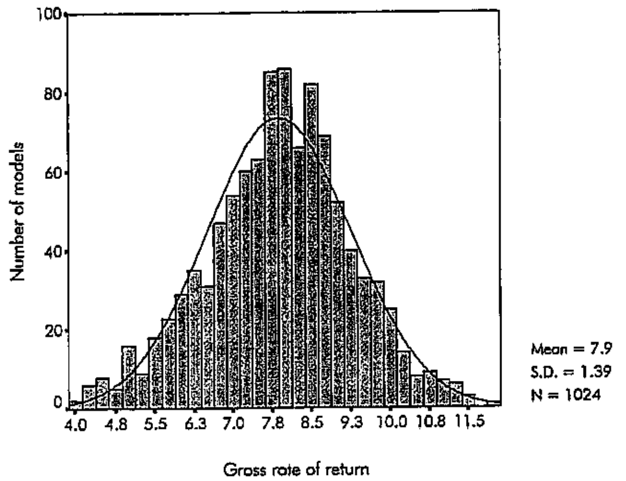
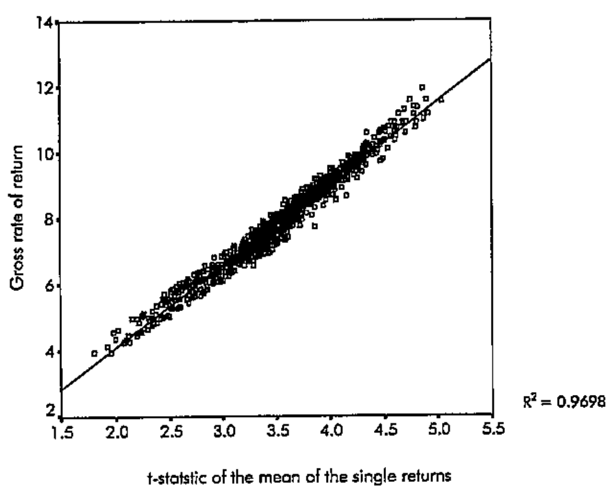
[12]) The Sharpe ratio is mostly used to compare the return (in excess of the risk-free rate) and risk of holding different assets over a certain period by calculating, e.g., the mean and standard deviation of daily returns. In this case the number of single returns is the same for the assets under investigation 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).

Figure 3a: Distribution of trading systems by the gross rate of return
DM/dollar trading 1973 - 1999



These results indicate that there was little risk associated with technical currency trading over the past decades of floating exchange rates 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 only/mainly by chance (the issue of model selection and the ex-ante performance of technical models will be investigated later).

Figure 4a: Profitability and riskiness of 1024 technical trading systems
DM/dollar trading 1973 - 1999



The second source of risk of technical currency trading concerns the fact that every technical model produces sequences of (mainly) unprofitable positions which accumulate to substantial losses over the short run (this problem was already discussed when commenting on tables 1 and 2). 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 exchange rate trends over the long run.

3.2.2 *The performance by different types of models*

Tables 5a and 5b classify all models according to their performance as measured by the t-statistic into four groups and quantify the components of profitability for each of them. When trading in the DM/dollar market, 18.2% of all models achieve a t-statistic greater than 4 and the average (gross) rate of return per year over these modes amounts to 9.8%. The t-statistic of 38.7% of all models lies between 3.5 and 4 (average rate of return: 8.3%), 27.1% generate a t-statistic between 3 and 3.5% (average rate of return: 7.2%). The worst performing models, (t-statistic<3) with a share of 16.0%, still produce an average return of 5.7% per year.

The pattern of profitability is the same for each class of models. 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.

There is no clear relationship between the six components of the profitability of the models and their relative performance. The only exception concerns the duration of profitable and unprofitable positions, both of which are significantly lower in the case of the best performing models as compared to the average over all models. The fact that the duration of unprofitable positions produced by the best models deviates from the average to a greater extent than the duration of profitable positions seems to be the most important reason for their higher profitability (it reflects the popular principle of technical trading "cut losses short and let the profits run").

Models operating with a lag of signal execution by one day produce significantly less trades than in the case of instantaneous executions (as has to be expected). However, the average profitability of the models is slightly reduced by this delay filter (from 8.3% to 7.5% per year), mainly because it increases on average the duration of unprofitable positions to a greater extent than the duration of profitable positions.

Table 5a: Components of the profitability of trading systems by duration of profitable positions
Moving average and momentum models

DM/dollar-trading 1973-1999

t-statistic of the Mean of the single returns	Number of models		Mean and standard deviation[1]) for each class of models							
	Absolute	Share in %	Gross rate of return	t-statistic	Profitable positions			Unprofitable positions		
					Number	Return per day	Duration in days	Number	Return per day	Duration in days
				All models						
< 3.0	164	16.0	5.69	2.616	5.82	0.065	56.91	7.26	–0.088	20.71
			(0.65)	(0.271)	(3.51)	(0.018)	(26.85)	(4.72)	(0.022)	(8.66)
3.0 - < 3.5	278	27.1	7.21	3.296	5.23	0.063	63.26	6.73	–0.083	20.58
			(0.42)	(0.135)	(3.82)	(0.017)	(22.61)	(5.73)	(0.023)	(7.07)
3.5 - < 4.0	396	38.7	8.34	3.717	5.99	0.069	53.83	7.84	–0.092	15.89
			(0.44)	(0.140)	(3.34)	(0.015)	(21.13)	(4.90)	(0.019)	(5.83)
> 4.0	186	18.2	9.83	4.289	7.16	0.075	43.54	11.19	–0.106	10.05
			(0.66)	(0.227)	(3.10)	(0.013)	(15.41)	(5.34)	(0.017)	(3.63)
Total	1,024	100.0	7.88	3.530	5.97	0.068	55.01	8.05	–0.091	16.87
			(1.39)	(0.548)	(3.52)	(0.016)	(22.63)	(5.41)	(0.022)	(7.48)
				Models with lag of signal execution = 0						
< 3.0	57	5.6	5.91	2.708	6.56	0.066	53.52	8.11	–0.092	18.70
			(0.46)	(0.199)	(4.28)	(0.019)	(27.64)	(5.35)	(0.023)	(8.76)
3.0 - < 3.5	101	9.9	7.12	3.291	5.86	0.065	62.10	7.72	–0.084	20.65
			(0.41)	(0.138)	(5.25)	(0.021)	(24.66)	(7.95)	(0.028)	(7.90)
3.5 - < 4.0	193	18.8	8.31	3.725	6.20	0.068	55.50	8.21	–0.091	16.40
			(0.47)	(0.149)	(4.14)	(0.017)	(23.32)	(6.19)	(0.023)	(6.57)
> 4.0	161	15.7	9.91	4.314	7.18	0.075	43.70	11.48	–0.107	9.67
			(0.66)	(0.231)	(3.16)	(0.013)	(15.44)	(5.42)	(0.016)	(3.56)
Total	512	50.0	8.31	3.711	6.48	0.070	52.87	9.13	–0.095	15.38
			(1.42)	(0.543)	(4.15)	(0.018)	(22.97)	(6.46)	(0.024)	(7.63)
				Models with lag of signal execution = 1						
< 3.0	107	10.4	5.57	2.567	5.42	0.064	58.71	6.81	–0.085	21.78
			(0.70)	(0.291)	(2.97)	(0.017)	(26.37)	(4.31)	(0.021)	(8.46)
3.0 - < 3.5	177	17.3	7.27	3.299	4.87	0.062	63.91	6.16	–0.083	20.53
			(0.42)	(0.134)	(2.64)	(0.015)	(21.41)	(3.85)	(0.019)	(6.58)
3.5 - < 4.0	203	19.8	8.37	3.709	5.78	0.069	52.25	7.49	–0.093	15.39
			(0.42)	(0.132)	(2.35)	(0.013)	(18.74)	(3.20)	0.014	(5.00)
> 4.0	25	2.4	9.30	4.130	7.04	0.076	42.49	9.33	–0.099	12.45
			(0.31)	(0.117)	(2.75)	(0.015)	(15.48)	(4.44)	(0.016)	(3.21)
Total	512	50.0	7.45	3.349	5.45	0.066	57.16	6.98	–0.088	18.36
			(1.22)	(0.492)	(2.66)	(0.015)	(22.10)	(3.81)	(0.018)	(7.03)

[1]) In parentheses.

Table 6a: Components of the profitability of trading systems by duration of profitable positions
Moving average models

DM/dollar-trading 1973-1999

t-statistic of the mean of the single returns	Number of models Absolute	Share in %	Gross rate of return	t-statistic	Profitable positions Number	Profitable positions Return	Profitable positions Duration	Unprofitable positions Number	Unprofitable positions Return	Unprofitable positions Duration
			Mean and standard deviation[1]) for each class of models							
					All Models					
< 3.0	155	16.4	5.67	2.604	5.86	0.065	56.55	7.23	–0.087	21.13
			(0.66)	(0.272)	(3.56)	(0.018)	(27.19)	(4.76)	(0.022)	(8.65)
3.0 - < 3.5	257	27.1	7.22	3.301	5.13	0.063	63.82	6.47	–0.082	21.11
			(0.42)	(0.136)	(3.65)	(0.017)	(22.60)	(5.23)	(0.022)	(6.94)
3.5 - < 4.0	375	39.6	8.34	3.717	5.92	0.069	54.48	7.68	–0.092	16.15
			(0.44)	(0.140)	(3.34)	(0.015)	(21.27)	(4.80)	(0.019)	(5.81)
> 4.0	161	17.0	9.82	4.275	6.79	0.075	45.45	10.74	–0.105	10.35
			(0.64)	(0.210)	(2.93)	(0.013)	(15.07)	(5.14)	(0.016)	(3.58)
Total	948	100.0	7.85	3.517	5.84	0.068	55.82	7.80	–0.091	17.32
			(1.38)	(0.543)	(3.44)	(0.016)	(22.62)	(5.16)	(0.021)	(7.47)
					Models with lag of signal execution = 0					
< 3.0	53	5.6	5.89	2.702	6.68	0.067	53.33	8.06	–0.091	19.38
			(0.47)	(0.204)	(4.42)	(0.019)	(28.66)	(5.55)	(0.024)	(8.71)
3.0 - < 3.5	95	10.0	7.12	3.289	5.51	0.064	63.85	7.03	–0.081	21.46
			(0.40)	(0.140)	(4.83)	(0.020)	(23.99)	(6.91)	(0.026)	(7.40)
3.5 - < 4.0	184	19.4	8.32	3.731	6.12	0.068	56.27	8.00	–0.090	16.77
			(0.47)	(0.149)	(4.16)	(0.017)	(23.41)	(6.12)	(0.023)	(6.49)
> 4.0	142	15.0	9.89	4.297	6.78	0.075	45.69	10.98	–0.106	10.06
			(0.64)	(0.213)	(2.97)	(0.013)	(15.09)	(5.21)	(0.016)	(3.58)
Total	474	50.0	8.28	3.697	6.26	0.069	54.29	8.70	–0.093	15.99
			(1.40)	(0.532)	(4.04)	(0.017)	(22.95)	(6.15)	(0.024)	(7.58)
					Models with lag of Signal Execution = 1					
< 3.0	102	10.8	5.55	2.552	5.44	0.064	58.23	6.80	–0.085	22.04
			(0.71)	(0.289)	(2.96)	(0.017)	(26.39)	(4.27)	(0.021)	(8.52)
3.0 - < 3.5	162	17.1	7.29	3.308	4.90	0.063	63.81	6.14	–0.082	20.91
			(0.41)	(0.133)	(2.72)	(0.015)	(21.82)	(3.92)	(0.019)	(6.67)
3.5 - < 4.0	191	20.1	8.36	3.704	5.72	0.069	52.76	7.37	–0.093	15.54
			(0.42)	(0.128)	(2.29)	(0.012)	(18.87)	(3.02)	(0.014)	(5.02)
> 4.0	19	2.0	9.29	4.107	6.85	0.075	43.65	8.94	–0.100	12.52
			(0.26)	(0.080)	(2.70)	(0.014)	(15.17)	(4.25)	(0.014)	(2.78)
Total	474	50.0	7.43	3.337	5.43	0.066	57.35	6.89	–0.088	18.65
			(1.22)	(0.492)	(2.64)	(0.015)	(22.20)	(3.73)	(0.018)	(7.12)

[1]) In parentheses.

Tables 6a and 7a show the components of profitability separately for moving average and momentum models (DM/dollar market). The overall performance of momentum models as measured by the annual rate of return and the t-statistic is slightly better than of moving average models, the profitability pattern of both types of models is, however, the same. The open positions of the best models last shorter than on average in either case (this is particularly true for the unprofitable positions), lagging the signal execution deteriorates the performance of both types of models.

Table 7a: Components of the profitability of trading systems by duration of profitable positions
Momentum models

DM/dollar-trading 1973-1999

t-statistic of the mean of the single returns	Number of Models		Gross rate of return	Mean and standard deviation[1] for each class of models						
	Absolute	Share in %		t-statistic	Profitable positions			Unprofitable positions		
					Number	Return per day	Duration in days	Number	Return per day	Duration in days
				All models						
< 3.0	9	11.8	6.07 (0.33)	2.824 (0.136)	5.02 (2.47)	0.055 (0.017)	62.94 (20.17)	7.88 (4.06)	–0.096 (0.017)	13.45 (5.13)
3.0 - < 3.5	21	27.6	7.09 (0.41)	3.244 (0.123)	6.47 (5.52)	0.065 (0.023)	56.29 (22.13)	9.88 (9.64)	–0.095 (0.027)	14.01 (5.17)
3.5 - < 4.0	21	27.6	8.31 (0.47)	3.712 (0.160)	7.21 (3.24)	0.072 (0.017)	42.21 (14.50)	10.74 (5.79)	–0.098 (0.019)	11.25 (3.96)
> 4.0	25	32.9	9.89 (0.81)	4.379 (0.306)	9.54 (3.17)	0.080 (0.015)	31.21 (11.58)	14.10 (5.82)	–0.111 (0.020)	8.10 (3.43)
Total	76	100.0	8.23 (1.47)	3.697 (0.589)	7.51 (4.15)	0.070 (0.020)	44.94 (20.32)	11.27 (7.14)	–0.101 (0.022)	11.24 (4.89)
				Models with lag of signal execution = 0						
< 3.0	4	5.3	6.10 (0.24)	2.785 (0.095)	5.02 (0.34)	0.052 (0.001)	55.99 (3.30)	8.75 (0.41)	–0.101 (0.005)	9.73 (0.52)
3.0 - < 3.5	6	7.9	7.21 (0.45)	3.325 (0.110)	11.38 (8.62)	0.081 (0.035)	34.47 (19.04)	18.58 (14.75)	–0.119 (0.040)	7.90 (3.37)
3.5 - < 4.0	9	11.8	8.03 (0.30)	3.607 (0.080)	7.84 (3.50)	0.070 (0.020)	39.72 (14.57)	12.47 (6.48)	–0.103 (0.020)	8.90 (2.41)
> 4.0	19	25.0	10.06 (0.83)	4.436 (0.317)	10.14 (3.03)	0.080 (0.015)	28.80 (8.36)	15.21 (5.66)	–0.115 (0.017)	6.79 (1.47)
Total	38	50.0	8.71 (1.59)	3.890 (0.639)	9.25 (4.55)	0.075 (0.021)	35.14 (14.23)	14.41 (7.85)	–0.111 (0.022)	7.78 (2.26)
				Models with lag of signal execution = 1						
< 3.0	5	6.6	6.05 (0.42)	2.856 (0.165)	5.03 (3.49)	0.058 (0.023)	68.50 (26.80)	7.18 (5.62)	–0.093 (0.024)	16.44 (5.24)
3.0 - < 3.5	15	19.7	7.04 (0.40)	3.212 (0.116)	4.50 (1.57)	0.058 (0.014)	65.02 (16.87)	6.39 (3.08)	–0.086 (0.013)	16.46 (3.43)
3.5 - < 4.0	12	15.8	8.53 (0.47)	3.791 (0.160)	6.73 (3.10)	0.073 (0.016)	44.08 (14.80)	9.44 (5.10)	–0.095 (0.019)	13.00 (4.05)
> 4.0	6	7.9	9.35 (0.47)	4.199 (0.188)	7.64 (3.11)	0.080 (0.018)	38.85 (17.32)	10.57 (5.23)	–0.095 (0.024)	12.24 (4.65)
Total	38	50.0	7.74 (1.18)	3.504 (0.466)	5.77 (2.83)	0.066 (0.018)	54.74 (20.91)	8.12 (4.62)	–0.091 (0.018)	14.70 (4.33)

[1] In parentheses.

3.2.3 *The pattern of profitability of technical trading models*

Figures 5a to 7a show the number, the daily return and the duration of profitable positions relative to the unprofitable positions for each of the 1024 models (DM/dollar trading). The models signal in almost all cases less profitable positions than unprofitable positions (the slope of the regression in figure 5a line is much smaller than 45^0).

Figure 5a: Frequency of profitable and unprofitable positions
DM/dollar trading 1973 - 1999

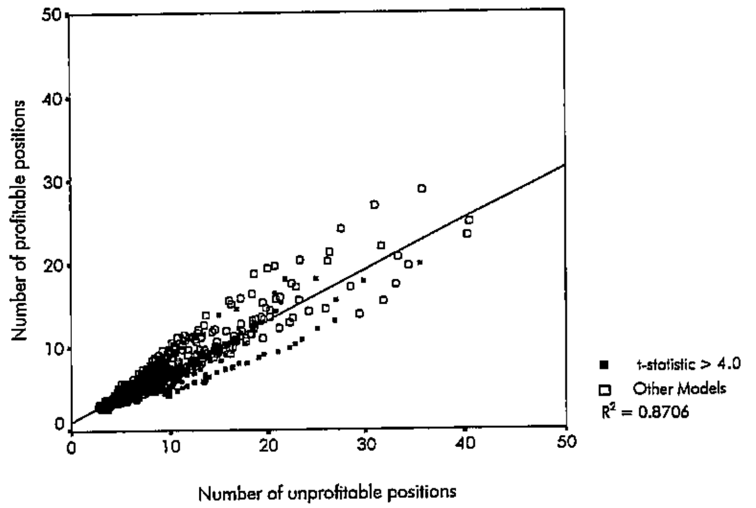
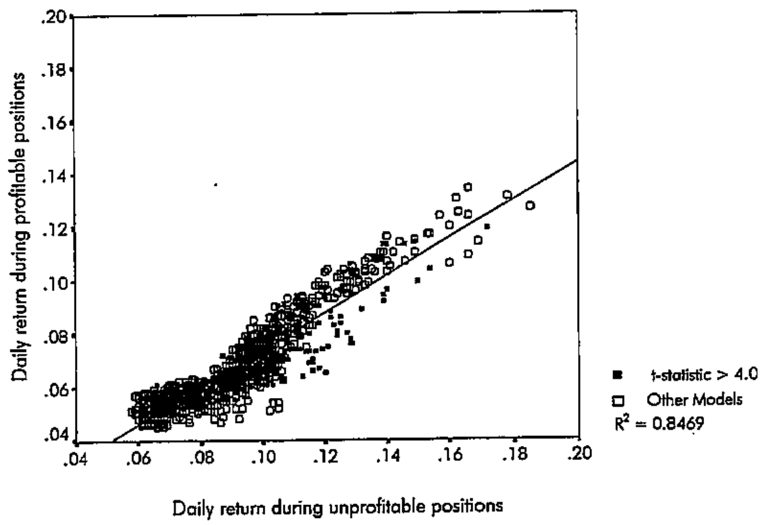


Figure 6a: Average daily return during profitable and unprofitable positions
DM/dollar trading 1973 - 1999



The average return per day during profitable positions is always lower than during unprofitable positions (figure 6a). The trading behavior of the best performing models (t-statistic>4.0) is not significantly different from the other models as far as these two pairs of profitability components are concerned. However, the ratio between the average duration of profitable and unprofitable positions is much higher in the case of the best performing model as compared to the average over all models (figure 7a).

Figure 7a: Average duration of profitable and unprofitable positions
DM/dollar trading 1973 - 1999

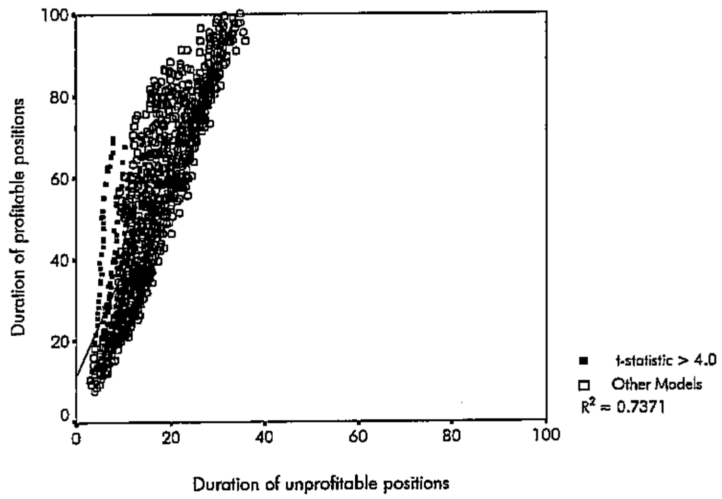
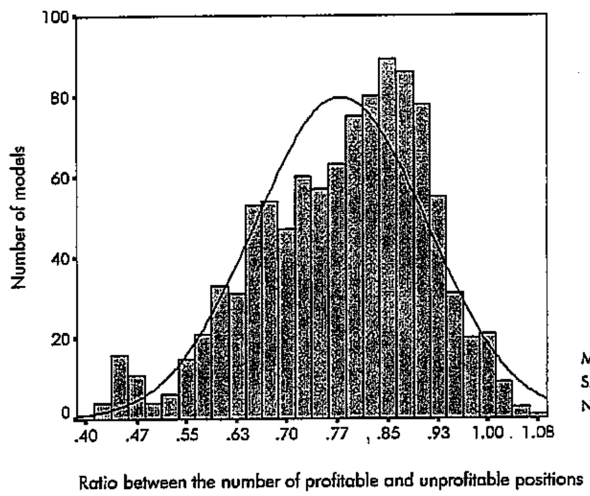
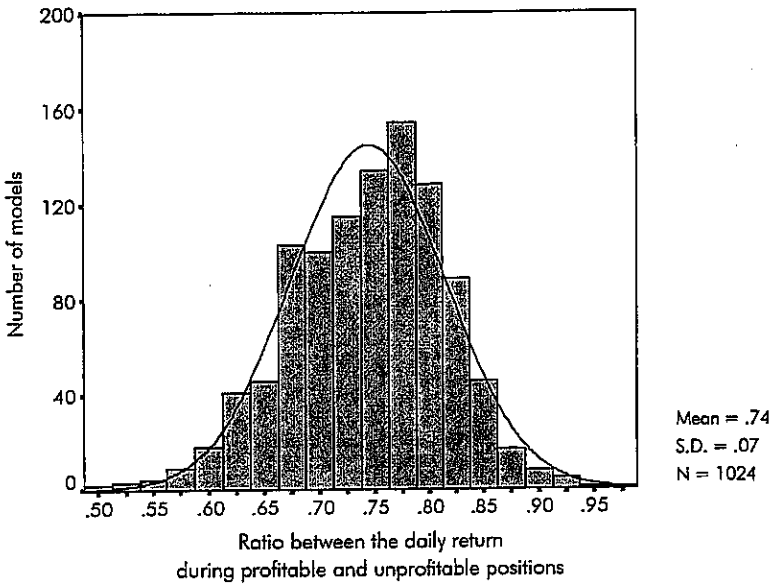


Figure 8a: Distribution of 1024 trading systems by the ratio between the number of profitable and unprofitable positions
DM/dollar trading 1973 - 1999



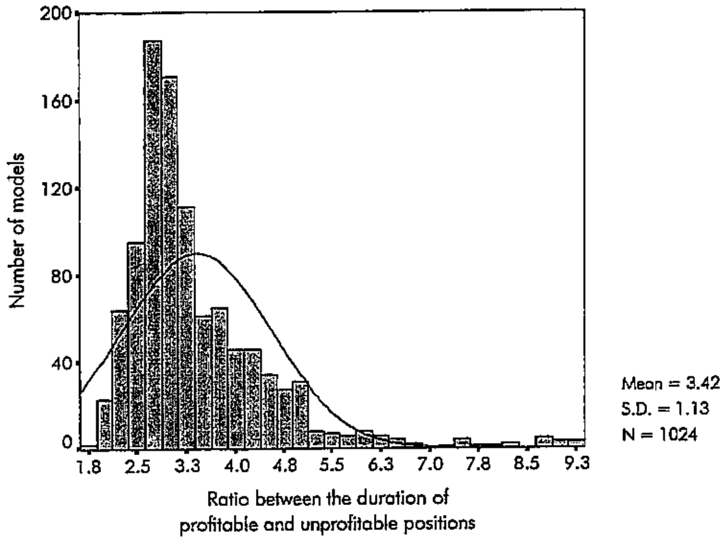
Two conclusions can be drawn from these observations. First, the profitability of technical currency trading in general stems from the successful exploitation of persistent exchange rate trends. Second, the best performing models minimize the duration of unprofitable positions (according to the rule "cut losses short and let profits run").

Figure 9a: Distribution of 1024 trading systems by the ratio between the daily return during profitable and unprofitable positions
DM/dollar trading 1973 - 1999



The distribution of the 1024 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 8a to 10a. 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 (0.78) as well as the mean of the ratio between the daily return during profitable and unprofitable positions (0.74) are lower than the mode and the median since very low values occur more frequently than implied by the normal distribution. These properties of the distributions of the two ratios as well as their low mean 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 currency trading to be excessively unprofitable if the duration of profitable and unprofitable were the same.

Figure 10a: Distribution of 1024 trading systems by the ratio between the duration of profitable and unprofitable positions
DM/dollar trading 1973 - 1999



However, as figure 10a shows, profitable positions last on average 3.42 times longer than unprofitable positions. At the same time the distribution of their ratio is extremely skewed to the right since very high ratios (up to a value of almost 10) occur abnormally frequently. Two conclusions can be drawn from these observations. First, the profitability of technical currency trading stems exclusively from the successful exploitation of persistent exchange rate 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.

Table 8a summarizes the results of splitting the overall profitability of technical currency trading into its components. Only 2.1% of all models produce a greater number of single profits than single losses (this share is slightly higher in the case of models which execute trading signals with a lag of 1 day). The daily return during profitable positions is in most cases (52.0%) by 20% to 30% lower than during unprofitable positions. For 65.7% of all models the average duration of profitable positions is between 2.5 and 4.0 times longer than the duration of unprofitable positions.

Table 8a: Distribution of technical trading systems by the ratio of the profit components
Moving average and momentum models

DM/dollar-trading 1973-1999

t-statistic of the mean of the single returns	NPP/NPL			RPP/RPL			DRP/DRL			DPP/DPL		
	<0.8	0.8 - 1.0	>1.0	<2.0	2.0 - 3.0	>3.0	<0.7	0.7 - 0.8	>0.8	<2.5	2.5 - 4.0	>4.0
	Relative frequency in %											
	All models											
< 3.0	32.9	67.2	–	56.7	42.1	1.2	17.7	72.0	10.4	34.8	61.0	4.3
3.0 - < 3.5	36.0	62.9	1.1	13.7	83.8	2.5	16.5	50.4	33.1	7.6	84.2	8.3
3.5 - < 4.0	51.0	44.7	4.3	13.9	71.2	14.9	27.5	49.2	23.2	11.1	68.2	20.7
> 4.0	82.3	16.7	1.1	5.9	46.2	47.8	46.2	42.5	11.3	5.4	37.1	57.5
Total	49.7	48.1	2.1	19.2	65.4	15.3	26.4	52.0	21.7	12.9	65.7	21.4
	Models with lag of signal execution = 0											
< 3.0	31.6	68.4	–	56.1	40.4	3.5	24.6	70.2	5.3	29.8	63.2	7.0
3.0 - < 3.5	34.7	65.3	–	12.9	85.1	2.0	7.9	49.5	42.6	7.9	86.1	5.9
3.5 - < 4.0	45.6	52.8	1.6	12.4	71.0	16.6	24.4	48.7	26.9	10.4	69.4	20.2
> 4.0	85.1	14.3	0.6	5.0	42.9	52.2	50.3	41.6	8.1	4.3	33.5	62.1
Total	54.3	44.9	0.8	15.0	61.5	23.4	29.3	49.0	21.7	10.2	60.7	29.1
	Models with lag of signal execution = 1											
< 3.0	33.6	66.4	–	57.0	43.0	–	14.0	72.9	13.1	37.4	59.8	2.8
3.0 - < 3.5	36.7	61.6	1.7	14.1	83.1	2.8	21.5	50.8	27.7	7.3	83.1	9.6
3.5 - < 4.0	56.2	36.9	6.9	15.3	71.4	13.3	30.5	49.8	19.7	11.8	67.0	21.2
> 4.0	64.0	32.0	4.0	12.0	68.0	20.0	20.0	48.0	32.0	12.0	60.0	28.0
Total	45.1	51.4	3.5	23.4	69.3	7.2	23.4	54.9	21.7	15.6	70.7	13.7

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

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

The better is the performance of technical models (as measured by the t-statistic) the longer is the average duration of their profitable positions relative to the unprofitable positions. However, there is no clear relationship between the performance of the trading models and the two other pairs of profitability components (table 8a). The simulation of the trading behavior of the 1024 models in the yen/dollar market shows a picture very similar to the performance of the models in the DM/dollar market. The relative share of models with a t-statistic greater than 4.0 and smaller than 3.0 amounts to 15.4% and 11.6%, respectively (somewhat less than in the case of DM/dollar trading). Lagging the signal execution by one day slightly reduces the profitability also when trading in the yen/dollar market (table 5b). In contrast to the results for the DM/dollar market, the moving average models perform better than the momentum models when trading in the yen/dollar market (the former produce an average return of 9.1%, the latter 8.5% - tables 6b and 7b).

Also the pattern of profitability of the 1024 models when trading in the yen/dollar market is very similar to that observed when trading in the DM/dollar market (table 8b and figures 5b to 10b). In the case of yen/dollar trading the average ratio between the number of profitable and unprofitable positions amounts to 0.76 (DM/dollar: 0.78), and the ratio between the daily return during profitable and unprofitable positions to 0.82 (DM/dollar: 0.74). The overall profitability stems from the successful exploitation of persistent exchange rate trends which is reflected by the fact that the profitable positions last on average 3.45 times longer than the unprofitable positions (DM/dollar: 3.42).

The trading behavior of the models in the yen/dollar market differ from that in the DM/dollar market only in two respects. First, there is no tendency in yen/dollar trading for models to perform better the higher is their ratio between the duration of profitable and unprofitable positions (table 8b). Second, the distributions of the ratios between the number of profitable and unprofitable positions as well as between the daily returns during profitable and unprofitable positions are less asymmetric as compared to the respective distributions in the case of DM/dollar trading (figures 8b and 9b).

3.2.4 *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 9a: Cluster of technical trading systems according to profit components
Moving average and momentum models

DM/dollar-trading 1973-1999

t-statistic of the mean of the single returns		Number of models	Mean of gross rate of return	Cluster center (mean) of profit components					
				Profitable positions			Unprofitable positions		
				Number	Return per day	Duration in days	Number	Return per day	Duration in day
< 3.0									
Cluster	1	50	5.91	10.11	0.088	25.79	12.80	–0.114	11.21
	2	50	5.78	5.13	0.062	49.85	6.34	–0.086	18.56
	3	64	5.44	3.00	0.049	86.73	3.66	–0.068	29.81
	Total	164	5.69	5.82	0.065	56.91	7.26	–0.88	20.71
3.0 - < 3.5									
Cluster	1	54	7.38	11.28	0.094	24.87	15.57	–0.121	9.55
	2	65	7.28	4.74	0.061	55.70	5.91	–0.081	18.78
	3	159	7.13	3.37	0.053	79.38	4.06	–0.071	25.06
	Total	278	7.21	5.23	0.063	63.26	6.73	–0.083	20.58
3.5 - < 4.0									
Cluster	1	121	8.43	9.76	0.087	28.30	12.95	–0.112	10.25
	2	161	8.50	4.96	0.065	54.86	6.43	–0.090	15.73
	3	114	8.01	3.44	0.055	79.48	4.41	–0.074	22.09
	Total	396	8.34	5.99	0.069	53.83	7.84	–0.92	15.89
> 4.0									
Cluster	1	88	9.84	9.54	0.086	29.54	14.74	–0.116	8.01
	2	97	9.82	5.04	0.066	55.95	8.03	–0.097	11.84
	3	1	9.25	3.89	0.058	71.15	5.55	–0.078	15.92
	Total	186	9.83	7.16	0.075	43.54	11.19	–0.106	10.05
Total									
Cluster	1	313	8.24	10.02	0.088	27.66	13.88	–0.115	9.65
	2	373	8.27	4.96	0.064	54.62	6.74	–0.090	15.63
	3	338	7.11	3.32	0.053	80.78	4.10	–0.071	24.93
	Total	1,024	7.88	5.97	0.068	55.01	8.05	–0.091	16.87

Table 9a shows the results of the cluster analysis. The 313 models of cluster 1 produce the highest number of open positions (23.9 per year on average), mainly for that reason the duration of profitable positions is relatively short (27.7 days on average). Cluster 1 comprises therefore those (fast) models which are most sensitive to price changes. The 373 models of cluster 2 signal 11.7 open positions per year, the profitable positions last 54.6 days on average. Cluster 3 comprises 338 (slow) models which produce only 7.4 open positions per year, their profitable positions last 80.8 days on average.

The average gross rates of return differ little across the three clusters, however, the sources of their profitability differ. The models of cluster 1 exploit primarily short-term exchange rate trends, those of cluster 2 specialize on medium-term trends, whereas the – slightly less profitable – models of cluster 3 exploit mainly long-term exchange rate trends (see also figure 11a). The daily returns during profitable and unprofitable positions differs significantly across the three clusters (they are the higher the shorter last the duration of the profitable and unprofitable positions).

Figure 11a: Three clusters of technical trading systems according to profit components
DM/dollar trading 1973 - 1999

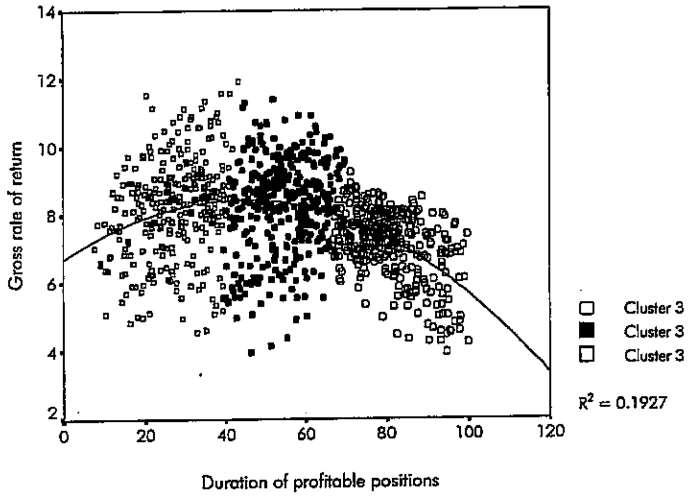


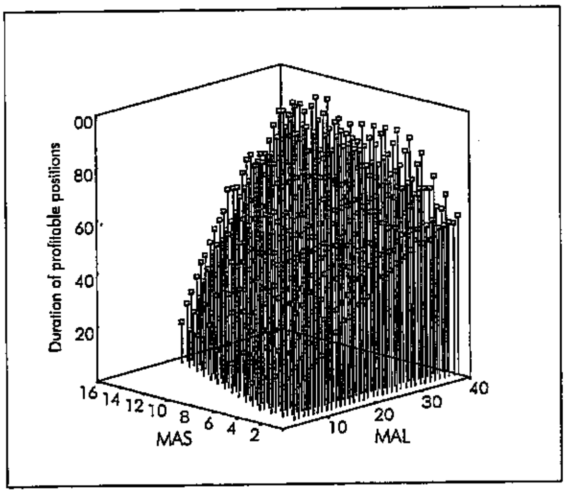
Table 9a classifies the models of the three clusters also according to their performance as measured by the t-statistic. The share of the (slow) models of cluster 3 is relatively high among those models with a t-statistic of less than 3.5 and relatively low among the other (better performing) models. Among the best models (t-statistic>4.0) only one model belongs to cluster 3, 88 models belong to cluster 1, and 97 to cluster 2. One can therefore conclude that the best performing models in the DM/dollar market specialize primarily on the exploitation of short-term and medium-term exchange rate trends.

The results of the cluster analysis for the models trading in the yen/dollar market are similar to those obtained for the DM/dollar market (table 9b and figure 11b), except for the fact that the best performing models in the yen/dollar market belong predominantly to clusters 2 and 3 (fast models perform relatively poorly when trading the yen/dollar exchange rate).

3.2.5 *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 12a and 12b), the number of open positions and 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).

Figure 12a: Duration of profitable positions and the parameter of trading systems
Moving average models with lag = 0
DM/dollar trading 1973 - 1999



Figures 13a and 13b show that the average duration of profitable positions produced by momentum models increases almost monotonically with the size of the time span i.

The relationship between the length of the long-term moving average and the profitability of moving average models (DM/dollar trading) is displayed in figure 14a taking the models with a short-term moving average of one day and instantaneous signal execution as examples. In this case the best performing models as measured by their annual gross rates of return are those which use a long-term moving average between 15 and 35 days.

Figure 13a: Profitability and parameter of trading systems
Moving average models with MAS = 1 and lag = 0
DM/dollar trading 1973 - 1999

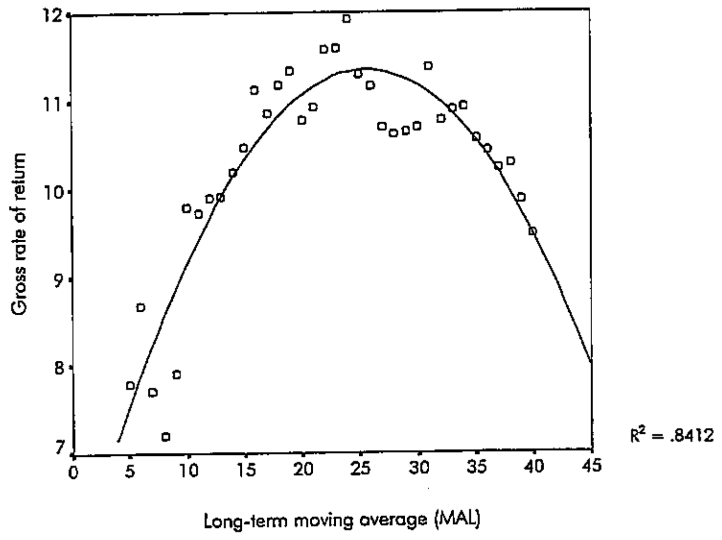


Figure 14a: Duration of profitable positions and the parameters of trading systems
Momentum models with lag = 0
DM/dollar trading 1973 - 1999

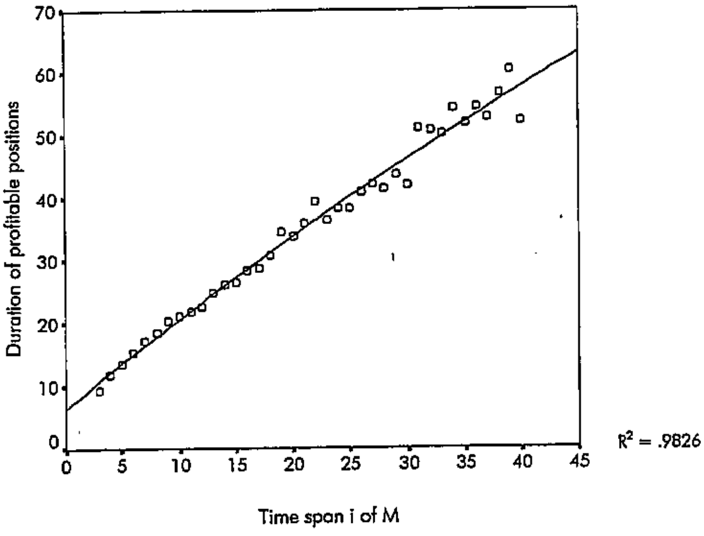
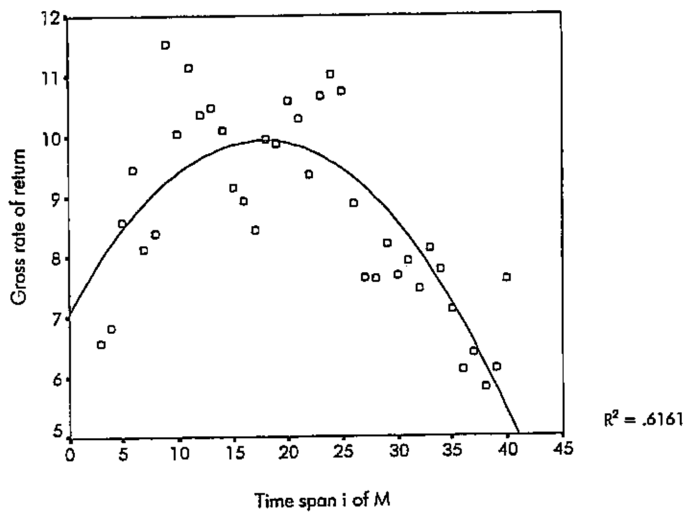


Figure 15a: Profitability and parameter of trading systems
Momentum models with lag = 0
DM/dollar trading 1973 - 1999



In the case of momentum models the highest profitability is achieved by those models which use a time span i between 10 and 25 days. However, the relationship between the performance of technical models and the size of their parameters is less close in the case of the momentum models as compared to the moving average models (this relationship is for both types of models looser when trading in the yen/dollar market than when trading in the DM/dollar market - figures 14b and 15b).

4. The performance of technical trading systems over subperiods in and out of sample

The study subdivides the overall sample period of 27 years (DM/dollar trading) into 7 subperiods each lasting 4 years except for the first subperiod which lasts for 3 years (1973/75, 1976/79, 1980/83, 1984/87, 1988/91, 1992/95, 1996/99). In the case of yen/dollar trading only the 6 subperiods beginning in 1976 are investigated.

First, I explore how all 1024 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).

Table 10a: Frequency and performance of stable and unstable trading Systems

DM/dollar-Trading 1973-1999

t-statistic of the mean of the single returns	Moving average and momentum models				Moving average models				Momentum models			
	Stable models[1]		Unstable models		Stable models[1]		Unstable models		Stable models[1]		Unstable models	
	Number	Gross rate of return	Number	Gross rate of return	Number	Gross rate of return	Number	Gross rate of return	Number	Gross rate of return	Number	Gross rate of return
< 3.0	47	5.60	117	5.72	46	5.59	109	5.70	1	6.12	8	6.06
3.0 - < 3.5	116	7.04	162	7.34	103	7.03	154	7.36	13	7.08	8	7.09
3.5 - < 4.0	95	8.06	301	8.43	85	8.04	290	8.43	10	8.28	11	8.34
> 4.0	63	10.08	123	9.70	45	10.07	116	9.72	18	10.10	7	9.36
Total	321	7.73	703	7.95	279	7.59	669	7.96	42	8.64	34	7.72
					Models with lag of signal execution = 0							
< 3.0	19	5.76	38	5.98	19	5.76	34	5.97	–	–	4	6.10
3.0 - < 3.5	49	6.98	52	7.26	44	6.94	51	7.27	5	7.34	1	6.57
3.5 - < 4.0	63	8.06	130	8.42	58	8.07	126	8.43	5	7.93	4	8.15
> 4.0	60	10.10	101	9.79	45	10.07	97	9.80	15	10.17	4	9.66
Total	191	8.19	321	8.38	166	8.05	308	8.40	25	9.15	13	7.86
					Models with lag of signal execution = 1							
< 3.0	28	5.49	79	5.60	27	5.47	75	5.58	1	6.12	4	6.03
3.0 - < 3.5	67	7.08	110	7.38	59	7.10	103	7.40	8	6.92	7	7.17
3.5 - < 4.0	32	8.06	171	8.43	27	7.95	164	8.43	5	8.64	7	8.45
> 4.0	3	9.75	22	9.24	–	–	19	9.29	3	9.75	3	8.95
Total	130	7.04	382	7.59	113	6.91	361	7.59	17	7.88	21	7.63

[1]) Stable models are profitable in each of the 7 subperiods, all others are unstable.

4.1 Performance of all models by subperiods

Table 10a shows that only 321 out of 1024 models produce a positive gross rate of return over each subperiod when trading the DM/dollar exchange rate. The average profitability of the stable and the unstable models is roughly the same. This holds true for all models with a t-statistic smaller than 4.0. As regards to the best performing models (t-statistic>4.0), however, the profitability of the stable models exceeds that of the unstable models for both types of trading systems, moving average models as well as momentum models.

If one classifies all models according to their average duration of profitable positions (DPP) into short-term models (DPP<30 days), medium-term models (30 days<DPP<60 days) and long-term models (DPP>60 days) the following picture emerges (table 11a). The great majority of short-term models (76.0%) and medium-term models (89.4%) are unstable, however, long-term models are more often stable than unstable (53.4% and 46.6%, respectively).

When trading in the yen/dollar market 780 models produce a positive gross return over each subperiod (table 10b). Hence, the performance of the technical models is much more stable in the yen/dollar market as compared to the DM/dollar market. The average profitability of stable models is roughly one percentage point higher than the profitability of unstable models (this holds true for moving average and momentum models, as well as for most classes of model performance according to the size of their t-statistic). As in the case of DM/dollar trading DM/dollar most unstable models are those (relatively fast) models which specialize on the exploitation of short-term and medium term price trends (almost all of the long-term models are stable when trading the yen/dollar exchange rate – table 11b).

Table 11a: Frequency and performance of stable and unstable trading systems by the duration of profitable positions

DM/dollar-trading 1973-1999

t-statistic of the mean of the single returns	Stable models		Unstable models	
	Number	Gross rate of return	Number	Gross rate of return
		Short-term models[1])		
< 3.0	2	6.67	31	5.90
3.0 - < 3.5	5	6.89	35	7.37
3.5 - < 4.0	15	8.49	48	8.38
> 4.0	20	9.97	19	9.41
Total	42	8.92	133	7.68
		Medium-term models[2])		
< 3.0	–	–	62	5.79
3.0 - < 3.5	4	7.47	53	7.34
3.5 - < 4.0	10	8.45	165	8.52
> 4.0	29	10.24	84	9.77
Total	43	9.57	364	8.17
		Long-term models models[3])		
< 3.0	45	5.55	24	5.32
3.0 - < 3.5	107	7.03	74	7.33
3.5 - < 4.0	70	7.91	88	8.29
> 4.0	14	9.90	20	9.68
Total	236	7.18	206	7.74

[1]) Average duration of profitable positions less than 30 days.

[2]) Average duration of profitable positions between 30 and 60 days.

[3]) Average duration of profitable positions greater than 60 days.

When trading the DM/dollar exchange rate almost all models are profitable over the first four subperiods, e.g., between 1973 and 1991 (table 12a). However, over the next following subperiod 62.2% of all models produce losses. These losses are in most cases relatively small so that the average return over all models amounts to only –1.24% with a standard deviation of 3.77. An inspection of figure 21a points to a number of possible explanations of the relative poor performance of technical currency trading between 1992 and 1995. First, exchange rate trends were steeper and shorter over this subperiod (as well as over the last subperiod 1996/99) when compared to the preceding 18 years (the performance of technical models improves as price trends become more persistent and smooth). Second, the size of countermovements during exchange rate trends as well as the size of short-term fluctuations ("whipsaws") were unusually large, causing technical models to produce many and relatively large single losses (as explained in section 3.1). The fact that long-term models performed comparatively better between 1992 and 1995 lends support to this explanation.

For similar reasons technical currency trading performed rather poorly between 1996 and 1999 even though only 9.4% of the models produced an overall loss.

As in the case of DM/dollar trading technical models perform comparatively poorly over the last three subperiods when trading in the yen/dollar. However, in contrast to DM/dollar trading they performed worst between 1996 and 1999 (rather than over the preceding subperiod DM/dollar. In this last subperiod the average return over all models amounts to only 3.16% with a standard deviation of 3.23 (17.7% of the models are unprofitable).

Summing up the performance of the 1024 models over 7 subperiods (DM/dollar trading) one can state that these models would have made losses in only 755 out of 7168 cases. In other words: if a technical trader had selected at random one out of the 1024 models for trading over each subperiod the expectational value of making a loss in one subperiod would have amounted to only 10.5%. The probability of making an overall loss over the entire sample period would have been practically nil. The same is true for trading the yen/dollar exchange rate since the models would have made losses in only 271 out of 6144 cases.

It is striking that the profitability of technical currency trading based on daily data has been declining over the sample period in both markets, the DM/dollar as well as the yen/dollar market. This tendency 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 the currency markets. However, the higher "speed" of currency transactions and the related shortening of the time horizon of expectations formation could account for the declining profitability of technical currency trading based on daily data in two different ways.

Table 12a: Performance of technical trading systems by subperiods
Moving average and momentum models

DM/dollar-trading 1973-1999

Subperiods	Number of models			Gross rate of return		t-statistic		Duration of profitable position	
	All	Profitable	Unprofitable	Mean	S. D.	Mean	S. D.	Mean	S. D.
1973 – 1975									
Short-term	127	127	0	21.87	3.76	2.402	0.292	20.77	5.86
Medium-term	333	333	0	25.95	2.41	2.648	0.260	47.28	8.38
Long-term	564	564	0	22.62	2.97	2.562	0.215	81.06	12.85
All	1,024	1,024	0	23.61	3.35	2.570	0.252	62.60	24.48
1976 – 1979									
Short-term	194	194	0	8.36	2.56	2.442	0.848	20.95	5.74
Medium-term	410	410	0	9.39	1.46	2.565	0.467	44.22	8.21
Long-term	420	420	0	7.32	2.21	1.693	0.547	85.35	13.48
All	1,024	1,024	0	8.35	2.22	2.184	0.718	56.68	27.37
1980 – 1983									
Short-term	140	139	1	11.80	3.89	2.122	0.710	21.86	5.39
Medium-term	504	501	3	8.68	2.62	1.514	0.470	46.76	8.57
Long-term	380	380	0	9.80	1.79	1.692	0.313	79.78	13.78
All	1,024	1,020	4	9.52	2.77	1.663	0.503	55.61	22.84
1984 – 1987									
Short-term	193	193	0	11.36	3.67	1.743	0.563	21.50	5.15
Medium-term	271	271	0	12.09	3.82	1.703	0.527	44.56	8.79
Long-term	560	560	0	7.99	2.96	1.057	0.395	80.33	12.23
All	1,024	1,024	0	9.71	3.85	1.357	0.572	59.77	26.01
1988 – 1991									
Short-term	163	144	19	5.38	3.78	0.845	0.591	22.22	5.68
Medium-term	504	504	0	8.42	2.54	1.292	0.384	45.73	8.69
Long-term	357	354	3	5.82	2.61	0.906	0.391	69.70	8.72
All	1,024	1,002	22	7.03	3.12	1.086	0.472	50.35	18.33
1992 – 1995									
Short-term	232	100	132	–0.17	3.75	–0.039	0.668	21.54	5.90
Medium-term	469	80	389	–3.19	3.81	–0.593	0.704	44.63	8.51
Long-term	323	207	116	0.83	1.83	0.180	0.381	71.04	8.66
All	1,024	387	637	–1.24	3.77	–0.223	0.703	47.73	19.90
1996 – 1999									
Short-term	222	150	72	1.16	2.97	0.268	0.652	21.81	5.39
Medium-term	369	353	16	3.18	1.89	0.720	0.421	45.53	9.14
Long-term	433	425	8	2.79	1.44	0.657	0.325	71.91	7.65
All	1,024	928	96	2.58	2.16	0.595	0.480	51.54	21.01

In the first case, one could argue that the information and communication technologies made currency 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 exchange rate movements to become more persistent and, hence, exploitable by technical models. As a consequence, exchange rate 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 exchange rates. 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 currency trading on the basis of daily as well as of intraday data. A simultaneous decline of the profitability of both, interday as well as and intraday trading, would lend support to the first hypothesis. By contrast, a rise in the profitability of technical currency trading on the basis of intraday data over the past 15 years would support the second hypothesis. However, an analysis of technical intraday trading in the foreign exchange market is beyond the scope of the present study.

The fact that all of the trading models produce excess returns over the entire sample period, the fact that this holds true in most cases when trading over different subperiods, as well as the specific pattern of the models' profitability, makes it rather implausible that the ex-post performance of technical currency trading is (mainly) the result of data snooping. To put it differently: if the DM/dollar as well as the yen/dollar exchange rate had actually followed a random walk, then a test of 1024 technical models over such a long sample period (covering 6837 and 6026 observations, respectively) could not have produced these results.

However, the fact that persistent exchange rate trends 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 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 exchange rate dynamics, namely, the occurrence of persistent price trends. The second component stems from the selection bias since a part of the importance of 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 exchange rate trends then it might be reproduced out of sample (provided that the lengths of the trends do not change strongly over time).

4.2 Performance of the best models in sample and out of sample

In order to investigate this matter, the following exercise was carried out. In a first step the single best and the 25 best models are identified on the basis of their ex-post performance as measured by the net rate of return. Two different test periods are used. The first consists of the most recent subperiod, the second of all past subperiods. Then the performance of the selected models is simulated over the subsequent subperiod.

Table 13a: Performance of the 25 most profitable trading systems over each subperiod
In sample and out of sample

DM/dollar-trading 1973-1999

Subperiods	Performance criterion I: Net rate of return over the preceding subperiod				Performance criterion II: Net rate of return over all past subperiods			
	In sample		Out of sample		In sample		Out of sample	
	Single best model	25 best models	Single best model	25 best models	Single best model	25 best models	Single best model	25 best models
1973 - 1975								
GRR	30.85	29.78			30.85	29.78		
t-statistic	3.060	2.939			3.060	2.939		
NRR	30.27	29.28			30.27	29.28		
DPP	41.39	48.47			41.39	48.47		
1976 - 1979								
GRR	15.35	12.69	8.56	9.13	19.64	18.48	8.56	9.13
t-statistic	4.187	3.670	2.226	2.485	3.879	3.905	2.226	2.485
NRR	14.40	11.97	7.56	8.40	19.00	18.01	7.56	8.40
DPP	19.34	31.57	24.80	38.99	33.53	48.00	24.80	38.99
1980 - 1983								
GRR	20.34	16.97	8.60	9.35	16.75	15.93	10.97	9.48
t-statistic	3.387	2.983	1.590	1.609	4.292	4.294	1.975	1.658
NRR	18.85	15.74	7.73	8.65	16.01	15.32	10.34	8.94
DPP	16.75	22.77	23.95	35.18	33.76	42.24	38.24	47.89
1984 - 1987								
GRR	21.85	19.43	13.60	13.20	17.29	16.09	15.73	13.31
t-statistic	2.842	2.707	2.101	1.976	5.180	4.660	2.339	1.852
NRR	21.07	18.50	11.91	11.79	16.30	15.35	14.82	12.63
DPP	37.06	32.88	15.34	21.56	26.48	40.62	26.55	40.80
1988 - 1991								
GRR	14.50	13.29	12.90	8.93	16.02	14.82	5.70	9.57
t-statistic	2.190	2.027	2.110	1.423	5.068	4.977	0.931	1.520
NRR	14.05	12.72	12.01	7.91	15.30	14.10	4.67	8.77
DPP	48.82	47.93	36.69	33.52	45.71	43.49	29.11	40.03
1992 - 1995								
GRR	10.18	7.62	–7.27	–3.96	12.88	12.23	–1.81	–2.09
t-statistic	1.743	1.333	–1.282	–0.707	4.621	4.639	–0.318	–0.385
NRR	8.84	6.70	–7.84	–4.68	12.09	11.40	–2.94	–3.04
DPP	16.73	35.28	46.21	43.45	44.13	39.92	36.52	36.86
1996 - 1999								
GRR	8.66	7.26	5.40	2.98	11.92	11.03	6.41	3.86
t-statistic	1.852	1.580	1.197	0.679	4.853	4.698	1.512	0.890
NRR	8.28	6.82	3.96	2.05	11.11	10.21	5.51	2.89
DPP	56.50	55.16	16.42	38.13	43.18	42.56	38.04	35.53

Table 14a: Pattern of profitability of the 25 best performing trading systems
Performance criterion I: Net rate of return over the preceding subperiod
In sample
DM/dollar-trading 1973-1999

Subperiods	Number	Gross rate of return	t-statistic	Net rate of return	Mean over each class of models: Profitable positions: Number	Return per day	Duration in days	Unprofitable positions: Number	Return per day	Duration in days
1973 – 1975										
Short-term models	1	30.45	2.930	29.54	12.69	0.111	24.92	10.02	–0.092	4.87
Medium-term models	22	29.79	2.949	29.30	6.69	0.105	48.28	5.54	–0.065	10.31
Long-term models	2	29.34	2.835	28.92	5.18	0.101	62.35	5.51	–0.072	9.90
1976 – 1979										
Short-term models	13	13.03	3.997	12.14	13.82	0.056	22.00	8.41	–0.050	8.32
Medium-term models	9	12.44	3.464	11.84	8.98	0.052	33.01	6.22	–0.040	11.36
Long-term models	3	11.94	2.873	11.61	4.33	0.046	68.71	3.75	–0.024	18.34
1980 – 1983										
Short-term models	23	17.16	3.034	15.86	15.20	0.109	18.85	17.27	–0.146	5.51
Medium-term models	1	15.01	2.603	14.39	7.99	0.070	36.22	7.49	–0.070	10.10
Long-term models	1	14.60	2.201	14.36	3.25	0.058	99.62	2.75	–0.103	15.18
1984 – 1987										
Short-term models	9	19.00	2.845	17.77	12.77	0.118	23.58	18.00	–0.157	5.15
Medium-term models	16	19.67	2.629	18.92	7.71	0.101	38.10	11.28	–0.122	7.34
Long-term models	–	–	–	–	–	–	–	–	–	–
1988 – 1991										
Short-term models	–	–	–	–	–	–	–	–	–	–
Medium-term models	22	13.35	2.049	12.76	6.31	0.083	45.83	8.45	–0.119	11.41
Long-term models	3	12.84	1.870	12.43	4.01	0.084	63.37	6.26	–0.077	17.72
1992 – 1995										
Short-term models	9	7.98	1.372	6.62	14.77	0.116	16.36	19.38	–0.136	7.38
Medium-term models	16	7.41	1.311	6.74	6.39	0.060	45.92	10.44	–0.120	8.19
Long-term models	–	–	–	–	–	–	–	–	–	–
1996 – 1999										
Short-term models	2	7.30	1.564	6.50	9.76	0.080	22.81	10.39	–0.073	13.70
Medium-term models	14	7.30	1.586	6.88	4.88	0.054	55.30	5.68	–0.074	17.87
Long-term models	9	7.19	1.574	6.81	4.31	0.051	62.14	5.31	–0.067	18.60

Table 15a: Pattern of profitability of the 25 best performing trading systems
Performance criterion I: Net rate of return over the preceding subperiod
Out of sample
DM/dollar-trading 1976-1999

Subperiods	Number	Gross rate of return	t-statistic	Net rate of return	Mean over each class of models					
					Profitable positions			Unprofitable positions		
					Number	Return per day	Duration in days	Number	Return per day	Duration in days
1976 – 1979										
Short-term models	4	8.36	2.286	7.34	11.01	0.054	25.11	14.39	–0.071	6.43
Medium-term models	21	9.28	2.523	8.60	6.92	0.049	41.64	9.94	–0.058	8.81
Long-term models	–	–	–	–	–	–	–	–	–	–
1980 – 1983										
Short-term models	9	8.56	1.533	7.68	9.43	0.098	24.56	12.45	–0.103	10.95
Medium-term models	16	9.80	1.652	9.19	6.30	0.083	41.15	8.76	–0.097	12.99
Long-term models	–	–	–	–	–	–	–	–	–	–
1984 – 1987										
Short-term models	23	13.34	2.007	11.83	15.45	0.133	16.72	22.23	–0.176	5.43
Medium-term models	1	12.09	1.793	11.56	5.51	0.073	52.05	7.51	–0.113	10.43
Long-term models	1	11.27	1.440	11.01	2.75	0.070	102.27	3.76	–0.100	22.20
1988 – 1991										
Short-term models	7	6.88	1.075	5.52	12.13	0.102	23.54	21.87	–0.171	5.41
Medium-term models	18	9.72	1.559	8.84	7.52	0.085	37.40	14.59	–0.154	6.29
Long-term models	–	–	–	–	–	–	–	–	–	–
1992 – 1995										
Short-term models	3	–3.04	–0.536	–4.12	8.41	0.079	27.16	18.65	–0.153	7.80
Medium-term models	22	–4.08	–0.730	–4.76	5.22	0.059	45.67	11.69	–0.136	12.57
Long-term models	–	–	–	–	–	–	–	–	–	–
1996 – 1999										
Short-term models	9	2.22	0.497	0.84	12.95	0.089	17.71	21.57	–0.117	7.33
Medium-term models	12	3.19	0.733	2.50	5.86	0.048	45.36	11.49	–0.086	9.74
Long-term models	4	4.05	0.927	3.43	4.19	0.049	62.39	11.45	–0.084	9.09

Table 16a: Pattern of profitability of the 25 best performing trading systems
Performance criterion II: Net rate of return over all past subperiods
In sample
DM/dollar-trading 1973-1999

Subperiods	Number	Gross rate of return	t-statistic	Net rate of return	Mean over each class of models: Profitable positions: Number	Profitable positions: Return per day	Profitable positions: Duration in days	Unprofitable positions: Number	Unprofitable positions: Return per day	Unprofitable positions: Duration in days
1973 – 1975										
Short-term models	1	30.45	2.930	29.54	12.69	0.111	24.92	10.02	–0.092	4.87
Medium-term models	22	29.79	2.949	29.30	6.69	0.105	48.28	5.54	–0.065	10.31
Long-term models	2	29.34	2.835	28.92	5.18	0.101	62.35	5.51	–0.072	9.90
1973 – 1979										
Short-term models	–	–	–	–	–	–	–	–	–	–
Medium-term models	23	18.50	3.905	18.02	6.57	0.072	46.75	5.58	–0.051	11.72
Long-term models	2	18.25	3.899	17.88	4.93	0.067	62.33	4.08	–0.037	14.24
1973 – 1983										
Short-term models	2	16.52	4.458	15.47	11.40	0.094	24.21	15.04	–0.096	6.26
Medium-term models	23	15.87	4.280	15.30	6.73	0.075	43.81	7.53	–0.077	10.53
Long-term models	–	–	–	–	–	–	–	–	–	–
1973 – 1987										
Short-term models	3	16.59	5.030	15.57	10.86	0.094	25.94	14.69	–0.111	5.89
Medium-term models	22	16.02	4.610	15.32	6.92	0.082	42.62	10.62	–0.102	7.73
Long-term models	–	–	–	–	–	–	–	–	–	–
1973 – 1991										
Short-term models	3	14.83	5.143	13.73	11.61	0.095	23.65	15.86	–0.119	5.89
Medium-term models	22	14.82	4.954	14.15	6.32	0.079	46.20	10.26	–0.102	9.01
Long-term models	–	–	–	–	–	–	–	–	–	–
1973 – 1995										
Short-term models	4	12.55	4.862	11.45	10.93	0.094	24.79	16.34	–0.126	6.13
Medium-term models	20	12.19	4.606	11.40	6.92	0.078	41.83	13.02	–0.117	7.06
Long-term models	1	11.81	4.394	11.19	4.74	0.066	62.41	10.60	–0.111	6.55
1973 – 1999										
Short-term models	4	11.18	4.879	10.04	10.74	0.090	25.15	17.79	–0.123	5.79
Medium-term models	18	11.08	4.689	10.27	6.73	0.072	43.22	13.39	–0.114	6.26
Long-term models	3	10.60	4.513	10.06	4.64	0.064	61.82	9.09	–0.099	9.59

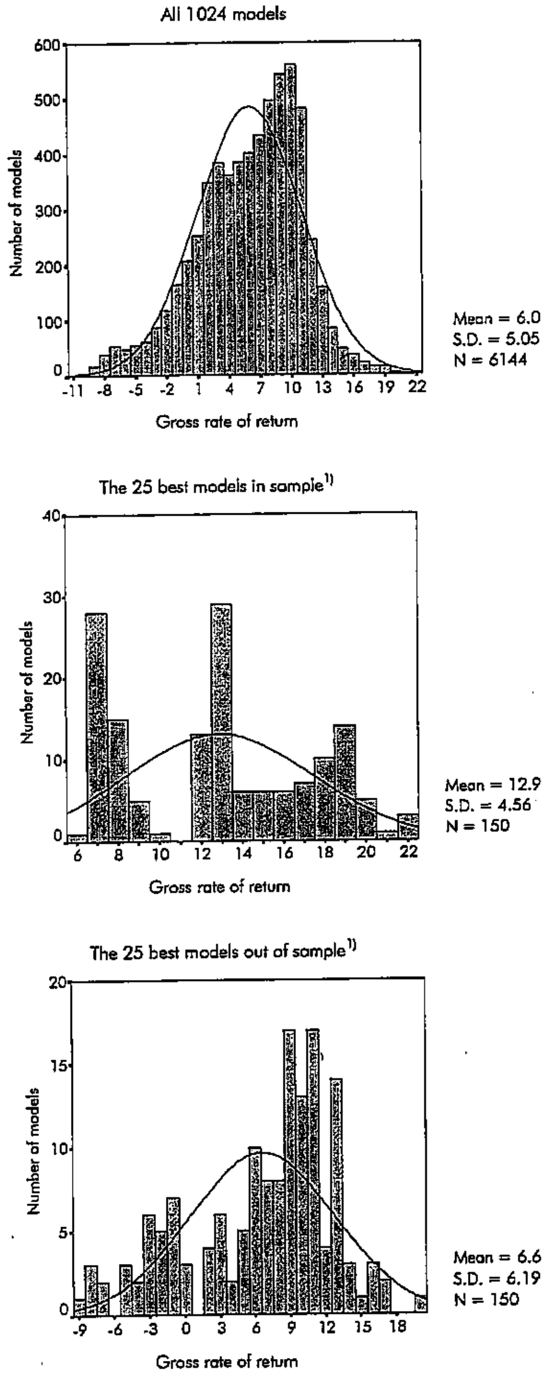
Table 17a: Pattern of profitability of the 25 best performing trading systems
Performance criterion II: Net rate of return over all past subperiods
Out of sample
DM/dollar-trading 1976-1999

Subperiods	Number	Gross rate of return	t-statistic	Net rate of return	Mean over each class of models					
					Profitable positions			Unprofitable positions		
					Number	Return per day	Duration in days	Number	Return per day	Duration in days
1976 – 1979										
Short-term models	4	8.36	2.286	7.34	11.01	0.054	25.11	14.39	–0.071	6.43
Medium-term models	21	9.28	2.523	8.60	6.92	0.049	41.64	9.94	–0.058	8.81
Long-term models	–	–	–	–	–	–	–	–	–	–
1976 – 1983										
Short-term models	–	–	–	–	–	–	–	–	–	–
Medium-term models	25	9.48	1.658	8.94	5.57	0.074	47.89	7.81	–0.098	13.24
Long-term models	–	–	–	–	–	–	–	–	–	–
1976 – 1987										
Short-term models	5	13.73	2.098	12.70	11.07	0.112	24.48	14.82	–0.162	7.04
Medium-term models	20	13.20	1.790	12.61	6.06	0.096	44.88	8.85	–0.121	11.72
Long-term models	–	–	–	–	–	–	–	–	–	–
1976 – 1991										
Short-term models	2	7.52	1.179	6.49	9.52	0.095	27.13	16.29	–0.156	6.66
Medium-term models	23	9.75	1.550	8.97	6.74	0.085	41.15	12.70	–0.137	7.98
Long-term models	–	–	–	–	–	–	–	–	–	–
1976 – 1995										
Short-term models	5	1.05	0.184	–0.23	10.14	0.090	24.14	21.88	–0.152	6.03
Medium-term models	20	–2.88	–0.527	–3.74	5.97	0.067	40.03	15.61	–0.143	9.52
Long-term models	–	–	–	–	–	–	–	–	–	–
1976 – 1999										
Short-term models	10	2.81	0.640	1.59	9.79	0.068	25.10	20.76	–0.110	6.04
Medium-term models	15	4.57	1.057	3.76	6.29	0.053	42.49	13.96	–0.091	7.80
Long-term models	–	–	–	–	–	–	–	–	–	–

Table 13a gives the main results for trading the DM/dollar exchange rate 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 single subperiods between 1976 and 1999 of 12.9%, whereas the average return of all models amounts to only 6.0% (table 18a and figure 16a). This difference is due to the "model mining" bias as will be shown below. Second, the out-of-sample profitability of the best model selected on the basis of their performance over the most recent subperiod (performance criterion I) is only slightly better than the average over the best 25 models (the single best model achieved ex-ante an average gross rate of return of 7.0% between 1976 and 1999, the 25 best models 6.6% - table 13a, figure 16a). Third, the best models selected according to their performance over all past subperiods (performance criterion II) produced slightly higher ex-ante returns (since these models are selected on the basis of a longer test period they are less affected by the "model mining" bias than the models selected according to the performance criterion I). Fourth, the single best model as well as the 25 best models produce ex-ante losses in only one subperiod (1992/95), their returns in all other subperiods are significantly positive. 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 1988/91, for example the duration of profitable positions of the best models (in sample) amounted to roughly 48 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 yen/dollar market except for the fact that the only subperiod over which the ex-ante returns are negative is the last one (table 13b and figure 16b).

Figure 16a: Distribution of trading systems by the gross rate of return DM/dollar trading over six subperiods between 1976 and 1999



[1]) According to Performance Criterion I.

Figure 16a compares the distribution of all models by their annual gross rates of return over the six subperiods between 1976 and 1999 with the respective distributions of the 25 best models according to performance criterion I in sample and out of sample. The distribution of the best models in sample shows two cases, those with a gross rate of return of 13% or less (these 50 cases concern the performance over the last two subperiods), and those with a gross rate of return of 15% or more. The mean return of the best models out of sample (6.6%) is only half as big as that of the best models in sample (12.9%). In 29 out of 150 cases the best models produce losses when trading out of sample (these losses occur only over the last two subperiods).

Figure 16b demonstrates that the performance of the 25 best models out of sample relative to in sample is much better in the case of yen/dollar trading as compared to DM/dollar trading. In the yen/dollar market the best models achieve an annual gross rate of return of 15.1% in sample and of 8.9% out of sample. When trading out of sample single losses occur in only 11 out of 125 cases.

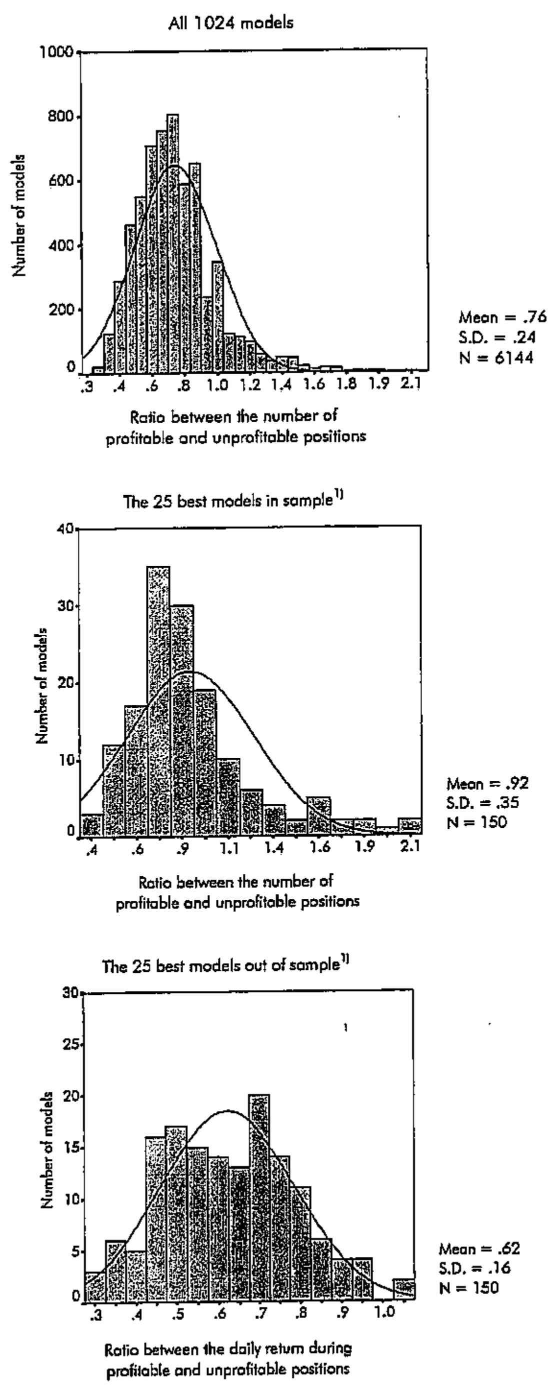
Tables 14a and 15a show the pattern of profitability of the 25 best performing models (performance criterion I) in sample and out of sample. The ratio between the average duration of profitable and unprofitable positions is roughly the same when simulating the selected models in sample and out of sample (in both cases the former lasts roughly four times longer than the latter). Hence, the property of technical models that accounts generally for their profitability can be reproduced out of sample and is therefore not to be considered a result of "model mining". By contrast, the ratio between the number of profitable and unprofitable positions as well as the ratio between the daily return during profitable and unprofitable positions are abnormally high in the case of the models which performed best ex ante (over the subperiod 1976/79 both ratios were even greater than one). This result is not reproduced out of sample and can therefore be attributed to "model mining".

A second possible reason for differences in the profitability of the best models in sample and out of sample could be related to changes in the lengths of price trends over time. This means that even if the phenomenon of persistent exchange rate trends occur frequently, it can not be exploited by technical models ex ante if the lengths of these trends change strongly between two consecutive periods. Suppose that in period A short-term trends dominate so that fast models perform best. These models would perform significantly worse than slow models over period B if exchange rate trends in this period are mainly long-term. However, this problem does not seem to be very important in the context of technical DM/dollar and yen/dollar trading. This becomes clear if one classifies the 25 best performing models according to the average length of their profitable positions into short-term, medium-term and long-term models. As one can see from tables 14a and 14b it never occurs that in one period mainly short-term (long-term) models are most profitable (in sample) and in the subsequent period mainly long-term (short-term) models.

The distribution of the ratio between the number of profitable and unprofitable positions as well as the distribution of the ratio between the daily return during profitable and unprofitable positions are much more skewed to the right in the case of the best models in sample as compared to the performance of these models out of sample (figures 17a, 17b and 18a, 18b). This demonstrates that the "model mining" bias affects specifically these two ratios. As a consequence, the means of these ratios are much higher in the case of the best models in sample than in the case of all models, and they are lowest in the case of the selected models out of sample.

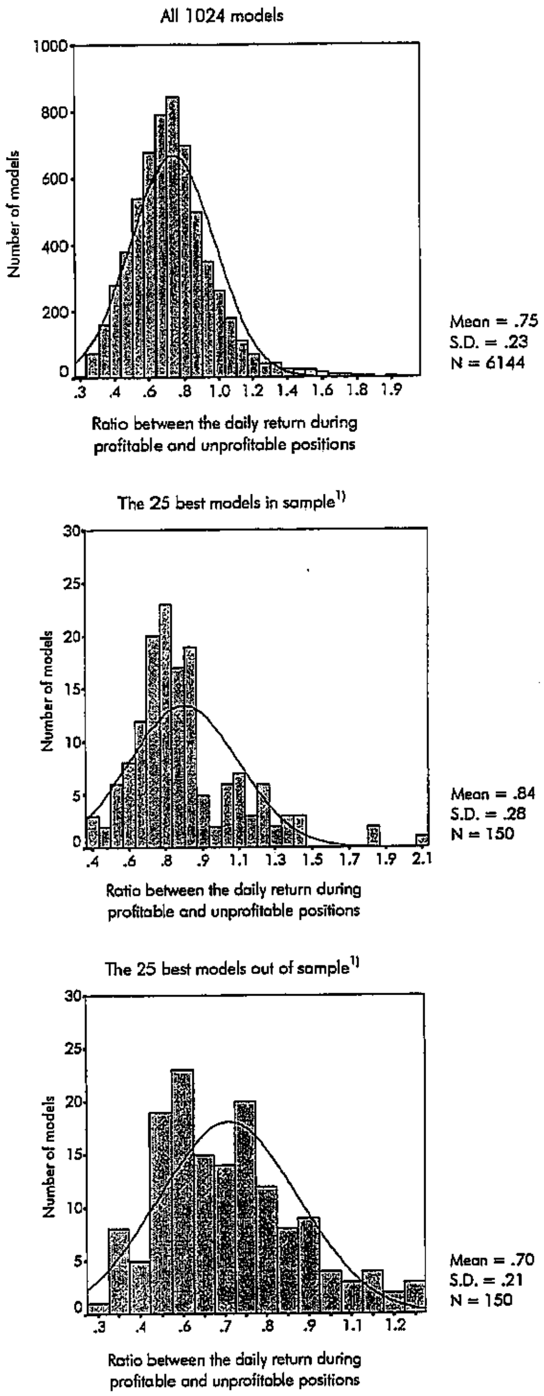
By contrast, the mean of the ratio between the average duration of profitable and unprofitable positions is even slightly higher in the case of the selected models out of sample as compared to their in sample performance (figures 19a and 19b). When trading DM/dollar, this ratio is also significantly higher in the case of the best models out of sample than in the case of all models (when trading the yen/dollar exchange rate it is only slightly lower). This implies that one can successfully optimize the ex-ante trading of technical models with respect to the exploitation of persistent exchange rate trends, i.e., with respect to those profit components which in general account for the profitability of technical currency trading.

Figure 17a: Distribution of trading systems by the ratio between the number of profitable and unprofitable positions
DM/dollar trading over six subperiods between 1976 and 1999



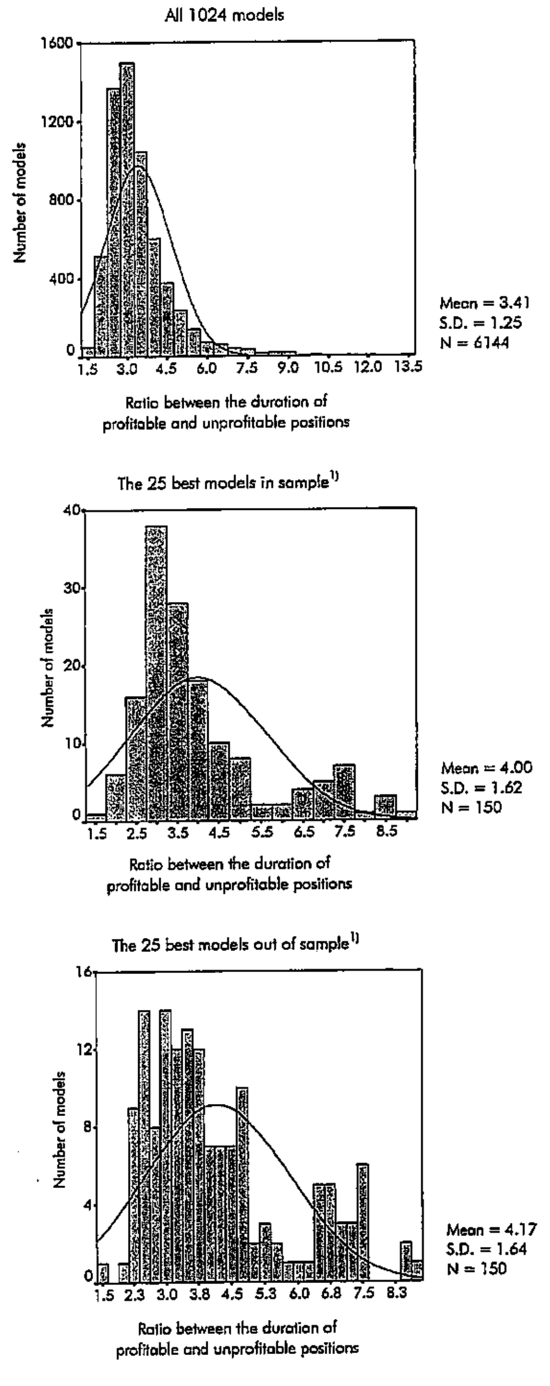
[1]) According to Performance Criterion I.

Figure 18a: Distribution of trading systems by the ratio between the daily return during profitable and unprofitable positions
DM/dollar trading over six subperiods between 1976 and 1999



¹) According to Performance Criterion I.

Figure 19a: Distribution of trading systems by the ratio between the duration of profitable and unprofitable positions
DM/dollar trading over six subperiods between 1976 and 1999



[1]) According to Performance Criterion I.

Tables 16a and 17a compare the pattern of profitability of the 25 best models selected according to performance criterion II in sample and out of sample. Since the model selection in this case is based on the performance over all past subperiods the ratio between the number of profitable and unprofitable positions as well as the ratio between the daily return during profitable and unprofitable positions of the best models in sample, the deviations the less from their normal values decline as the test period is lengthened. Hence, the selection process is progressively less affected by the "model mining" bias. This might explain why the best models selected according to performance criterion II performed better out of sample than those selected according to performance criterion I over the later subperiods (table 13a).

Table 18a: Distribution of trading systems by the gross rate of return and by the ratio of profit Components over six subperiods

DM/dollar-trading 1976-1999

Variable	Mean	S.D.	t-statistic
		All models (N = 6144)	
Gross rate of return	5.99	5.05	
NPP/NPL	0.760	0.237	
DRP/DRL	0.751	0.229	
DPP/DPL	3.412	1.253	
		The 25 most profitable models (N = 150) In sample	
Gross rate of return	12.88	4.56	18.234
NPP/NPL	0.920	0.349	5.584
DRP/DRL	0.844	0.279	4.049
DPP/DPL	4.001	1.624	4.410
		Out of sample according to performance criterion I (N = 150)	
Gross rate of return	6.61	6.19	1.217
NPP/NPL	0.623	0.162	-10.097
DRP/DRL	0.700	0.206	-2.987
DPP/DPL	4.168	1.638	5.613
		Out of sample according to performance criterion II (N = 150)	
Gross rate of return	7.21	5.51	2.684
NPP/NPL	0.605	0.180	–10.330
DRP/DRL	0.692	0.181	–3.916
DPP/DPL	4.598	1.420	10.133

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

The t-statistic tests for the significance of the difference between the mean of the four variables over the 150 cases of the best models (in and out of sample) and the respective mean over the 6144 cases of all models.

Tables 18a and 18b summarize the means over the gross rates of returns 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.

When trading DM/dollar, the means of all three ratios of the profit components are significantly higher in the case of the 25 best models in sample than in the case of all models. Consequently, the mean annual rate of return of the best models (12.9%) is more than twice as high than the mean over all models (6.0%).

The profitability pattern of the best models out of sample is very different. 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 significantly lower in the case of the best models out of sample as compared to the average ratios over all models. Hence, these differences are even greater between the best models out of sample and in sample. Since the high values of these two ratios observed in sample can not be reproduced out of sample they should be considered as a result of "model mining".

However, the ratio between the duration of profitable and unprofitable positions of the best models out of sample is even slightly higher than in sample and consequently significantly higher than in the case of all models. Hence, when trading the DM/dollar exchange rate that property of technical currency trading which in general accounts for its profitability, i.e., the longer duration of profitable positions relative to unprofitable positions, could be reproduced out of sample.

In the case of yen/dollar trading the results differ from those obtained from the simulation of DM/dollar trading in two respects. First, the ratio between the duration of profitable and unprofitable positions is smaller in the case of the best models in sample as compared to the performance of all models (however, it is still this ratio of profit components which accounts for the high profitability of the best models in sample since the product of the two other ratios amounts roughly to one). Second, the ratio between the daily returns during profitable and unprofitable positions of the best models out of sample is much less smaller than in sample (as compared to DM/dollar trading) and even slightly higher than the average over all models. As in the case of DM/dollar trading the ratio between the average duration of profitable and unprofitable positions of the best models out of sample is higher than in sample.

5. Aggregate positions and transactions of technical models and exchange rate dynamics

This section investigates the impact of the use of different trading models on exchange rate dynamics. In a first step an index of the aggregate transactions and open positions of the 1024 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. Based on this analysis one can estimate the extent to which the differential between the dollar interest rate and the DM (yen) interest rate impact upon the profitability of technical currency trading. Finally, the relationship between the level and the change of the net position index and the subsequent exchange rate movements is analyzed.

5.1 The aggregation of trading signals

The open positions of the 1024 trading models are aggregated in the following way. The number +1 (-1) is assigned to any long (short) position of each single model. The net position index is then calculated for every trading day as the sum of these numbers over all models divided by the number of models (1024). 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 1024 models change the open position from short to long (from long to short) between two consecutive days (implying 2048 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 1024 technical models at any point in time, whereas the net transaction index shows the excess demand for dollars (excess supply of dollars) stemming from these models. These indices are therefore used to evaluate the impact of the trading behavior of technical models upon exchange rate 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 on each trading day (divided by the number of all models). If, for example, 10% of all models switch from short to long positions on one day 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).

5.2 Similarities in position taking of technical models

Figure 20a shows the gradual adjustment of the 1024 technical models to exchange rate movements, using DM/dollar trading over the year 1992 as example. Due to a preceding depreciation trend almost all models hold a short position on January 2. The sharp upward movement of the DM/dollar rate between January 8, and 15, cause most models to switch their positions from short to long. This change begins on January 9, and ends on January 21, when roughly 93% of the models (PI=86.5) are holding long positions. However, 7% of the models – those which react most slowly to price changes – maintained short positions, since for these models the appreciation is not sufficiently strong given the pronounced depreciation over the last quarter of 1991 (figure 21a).

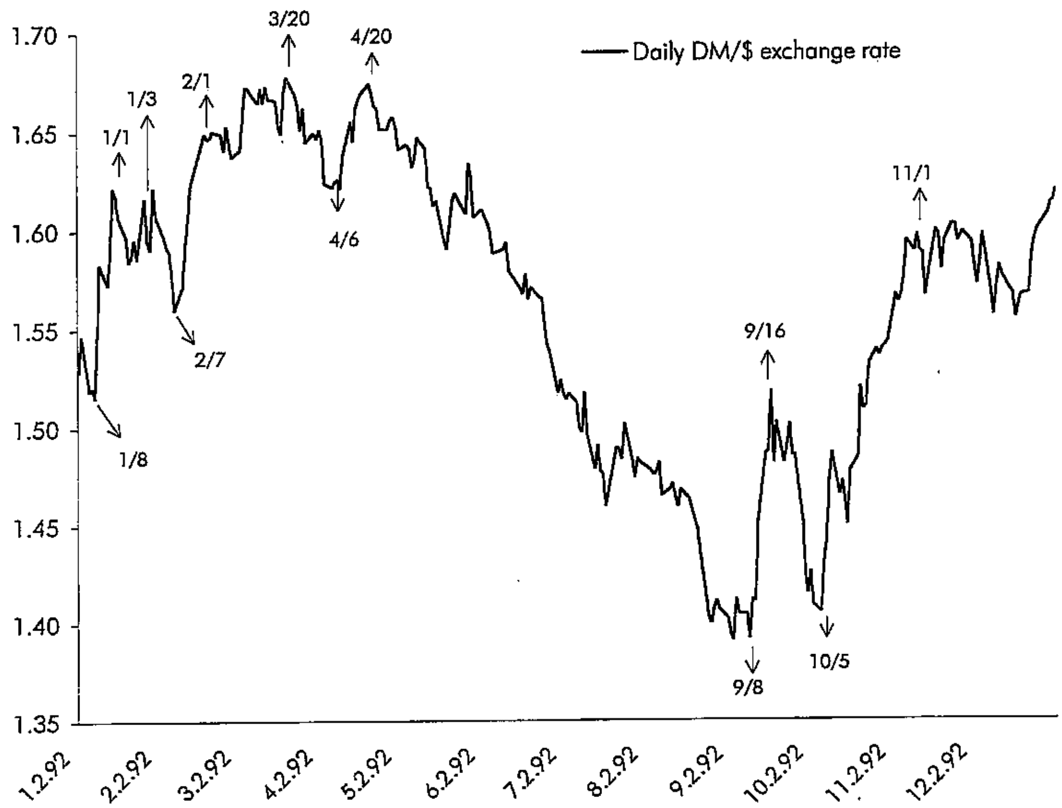
The sharp countermovement of the DM/dollar exchange rate between January 30, and February 7, induce almost 50% of the models to change their positions from long to short. These changes are quickly reversed due the subsequent appreciation which, however, loses momentum between February 18, and March 20. As a consequence, the depreciation between March 20, and April 6, is strong enough to cause most models to switch to short positions. During the depreciation trend of the dollar between April 20, and September 9, most models maintains short position (only the fastest models turn two times to long positions in reaction to relatively strong countermovements of the exchange rate). In a similar way almost all models hold a long position during the upward trend of the DM/dollar exchange rate between October 5, and November 10.

Figure 21a documents the relationship between exchange rate movements and the switching of 1024 trading systems over the entire sample period. Several observations can be made. First, most of the time the great majority of the models are on the same side of the market, either long or short. 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, do not occur (one would expect those situations to prevail if the exchange rate actually followed a random walk). Second, the process of changing open positions in response to a new exchange rate trend usually takes off 1 to 3 days after the local exchange rate maximum (minimum) has been reached (moving average models and momentum models are trend-following). Third, it takes between 10 and 20 trading days (2 to 4 weeks) 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 exchange rate trend, the trend often continues for some time (in such situations all models successfully exploit the trend).

The figures 20b and 21b show that the relationship between exchange rate movements and position switching on the part of the 1024 technical models for the yen/dollar market is very similar to the DM/dollar market.

Table 19a quantifies some of these observations. On 22.5% of all days of the entire sample period more than 95% of the models hold a long position (PI>90), and on 24.3% of all days more than 95% of the models hold a short position (PI<-90). Hence, on 46.8% of all days more than 95% of the models hold the same – long or short – position. 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 4.0% of all days. These situations occur primarily during the gradual 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).

Figure 20a: Aggregate trading signals and exchange rate dynamics
1992



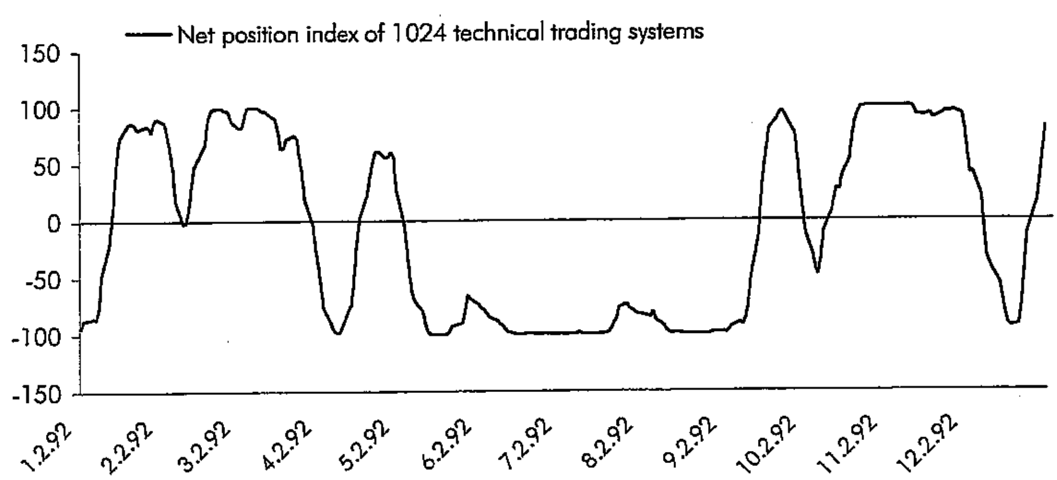
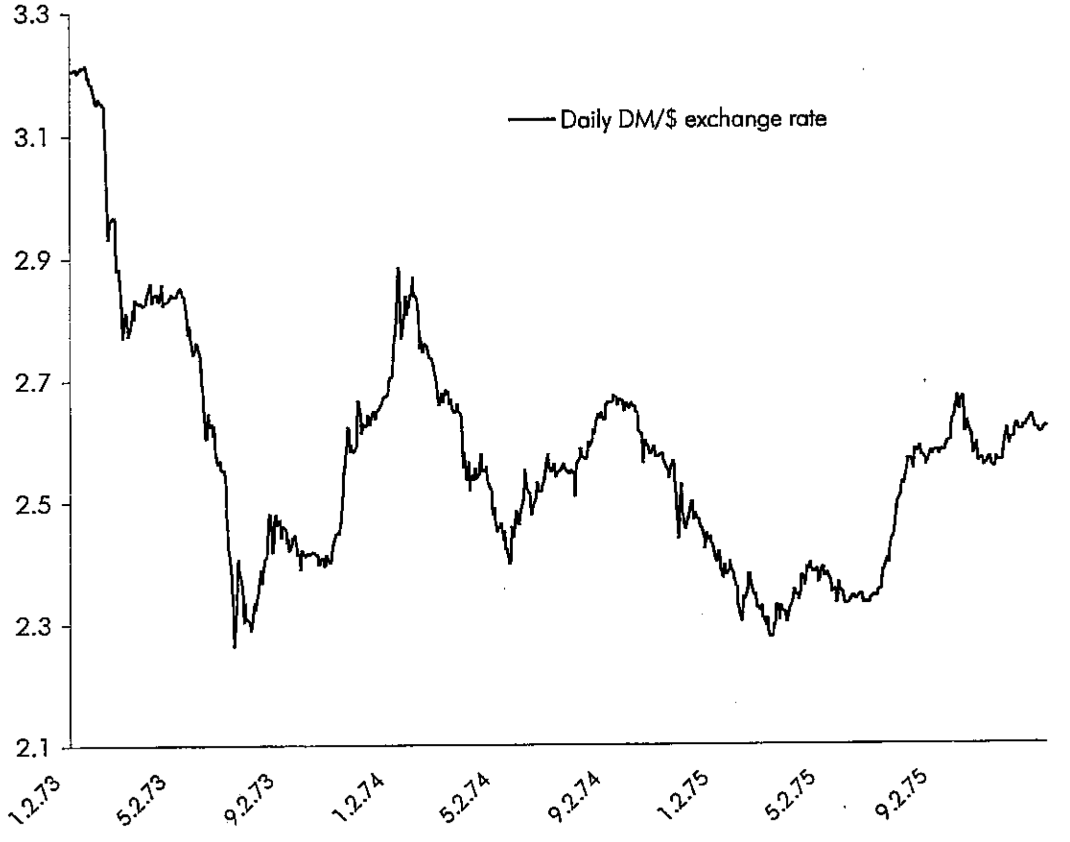


Figure 21a: Aggregate trading signals and exchange rate dynamics 1973-1975



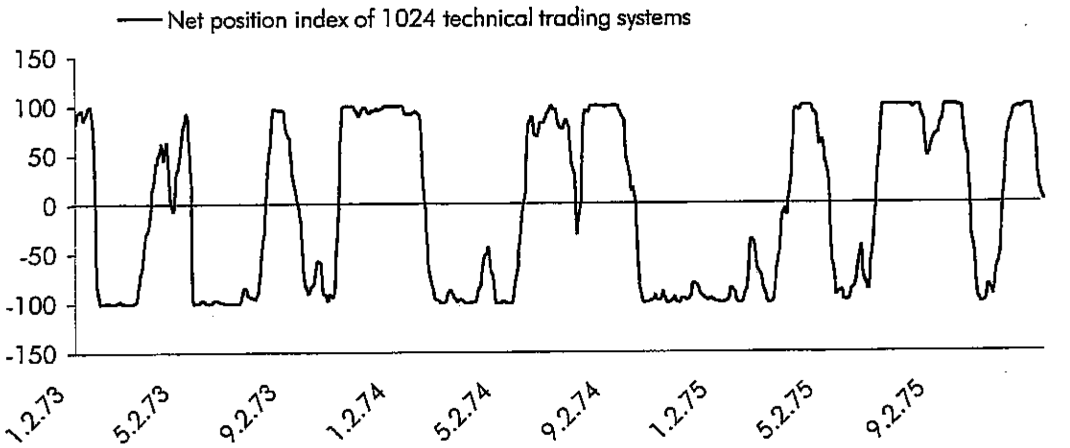
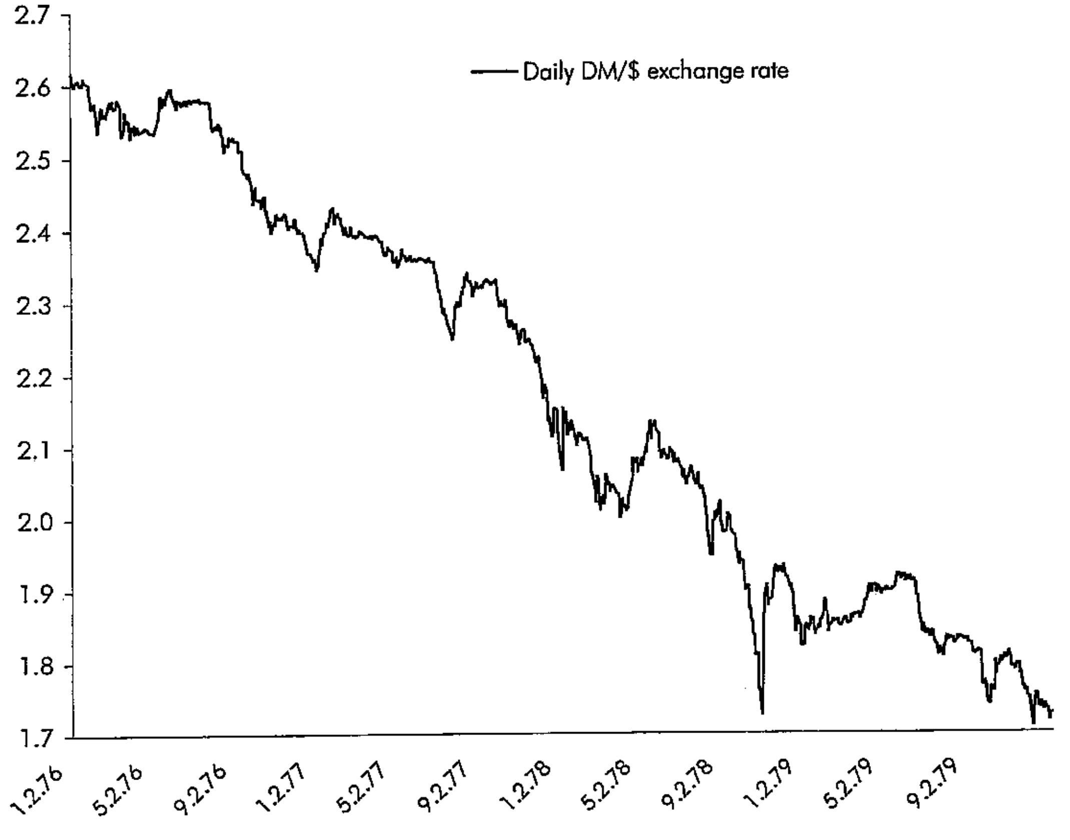


Figure 21a (cont.): Aggregate trading signals and exchange rate dynamics 1976-1979



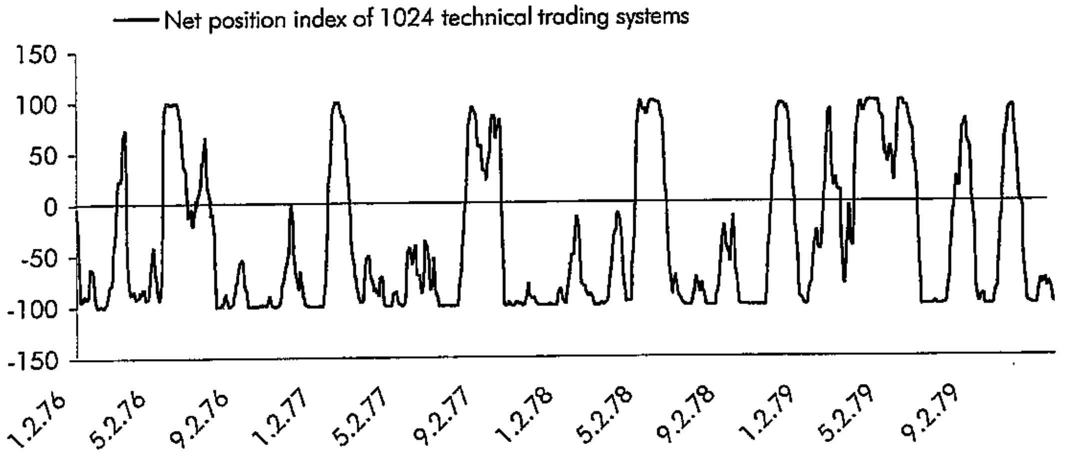


Figure 21a (cont.): Aggregate trading signals and exchange rate dynamics 1980-1983

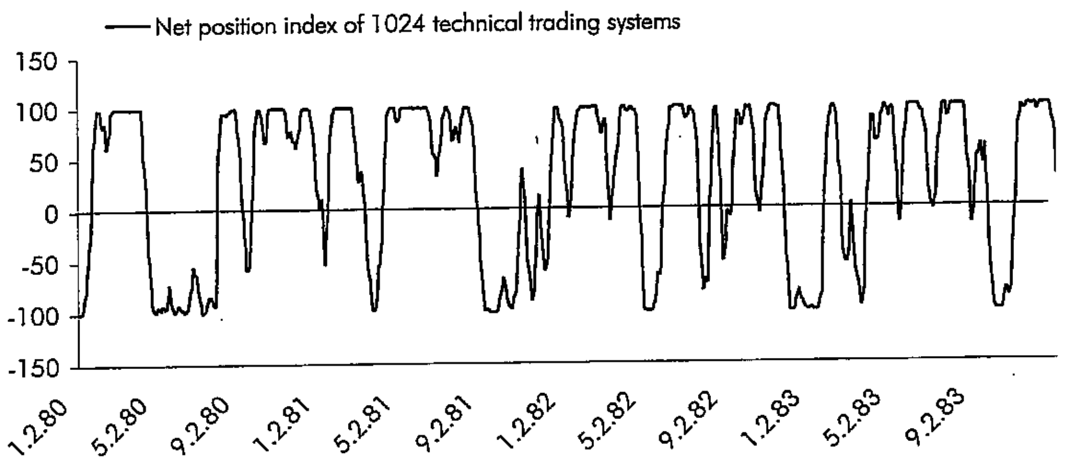
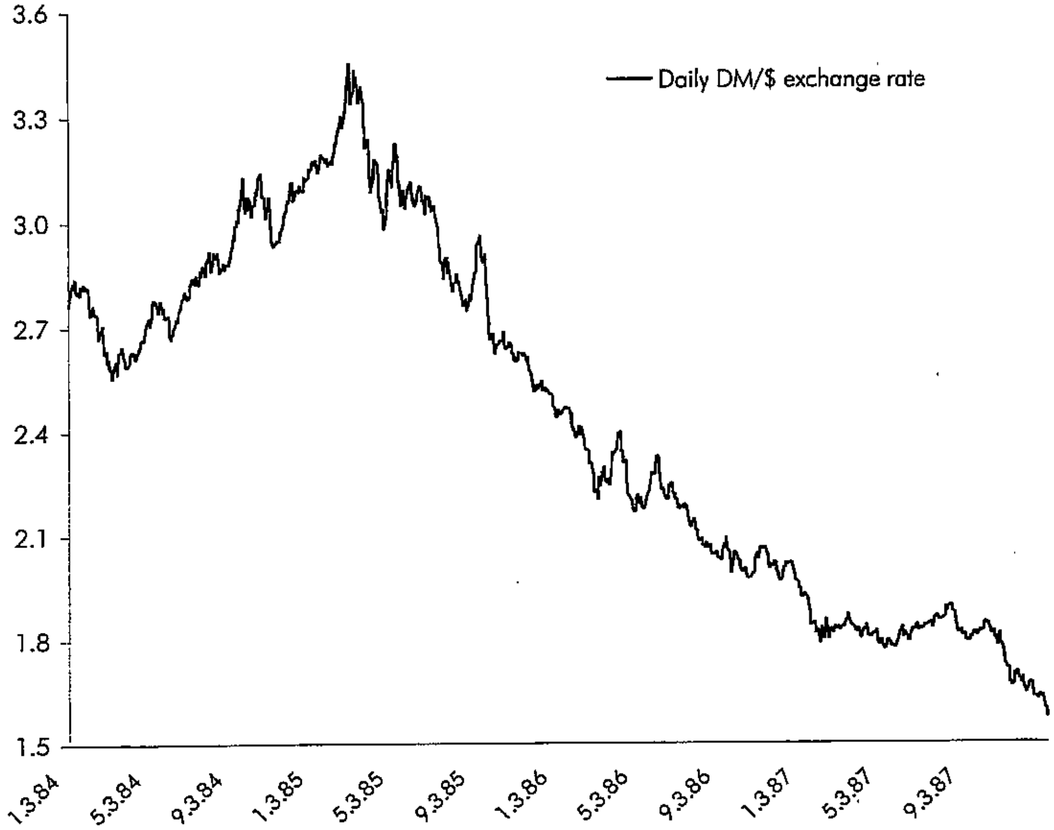


Figure 21a (cont.): Aggregate trading signals and exchange rate dynamics 1984-1987



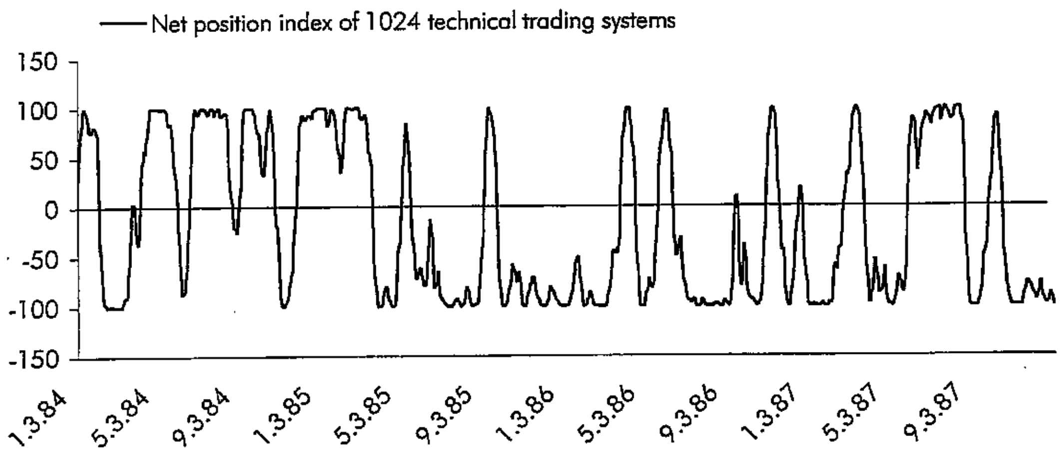
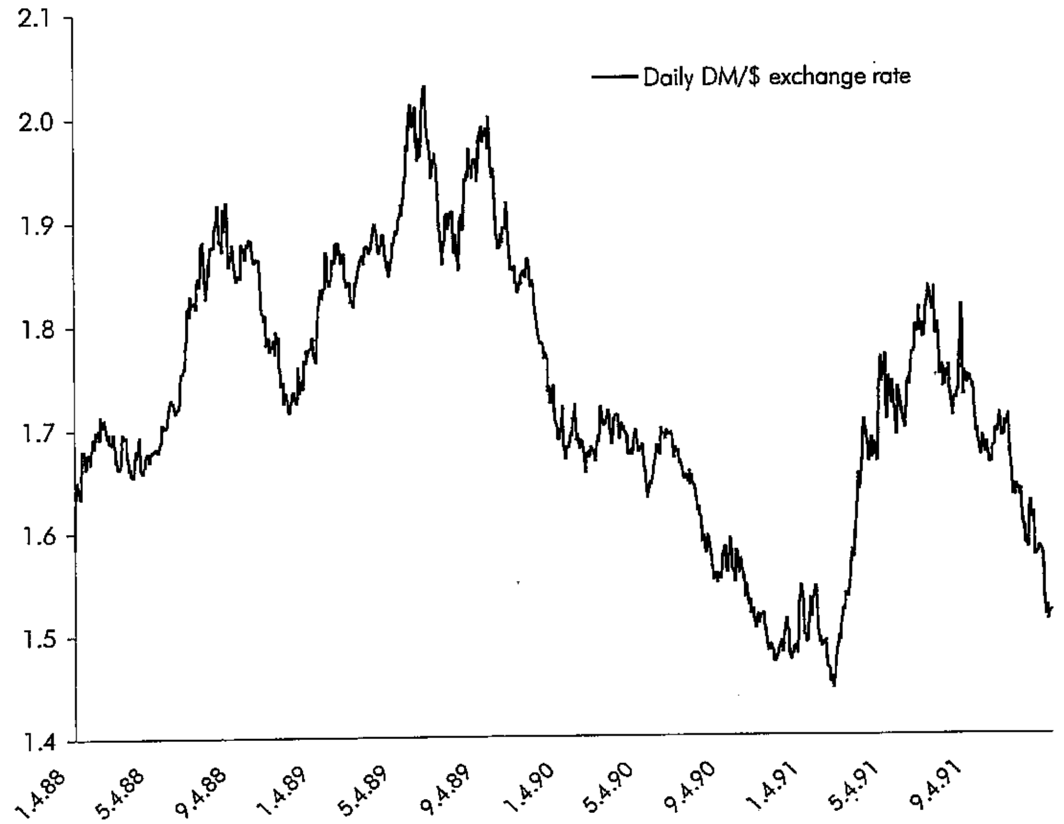


Figure 21a (cont.): Aggregate trading signals and exchange rate dynamics 1988-1991



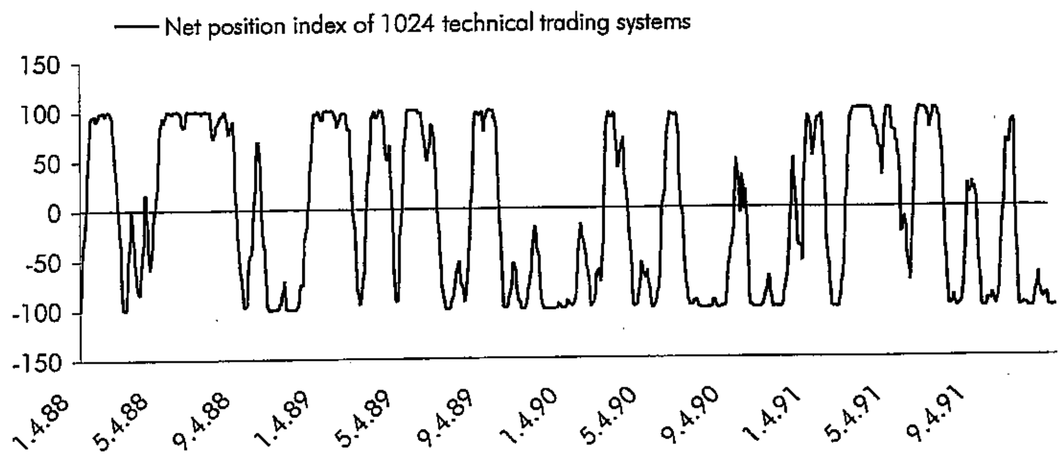
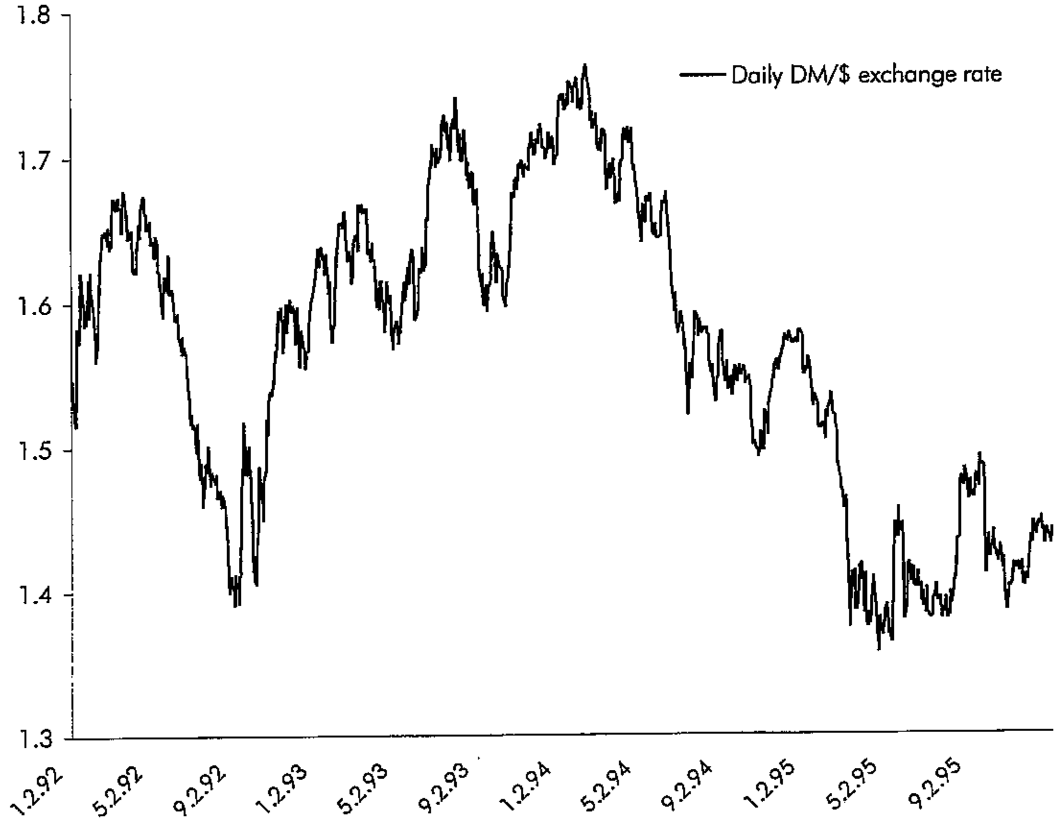


Figure 21a (cont.): Aggregate trading signals and exchange rate dynamics 1992-1995



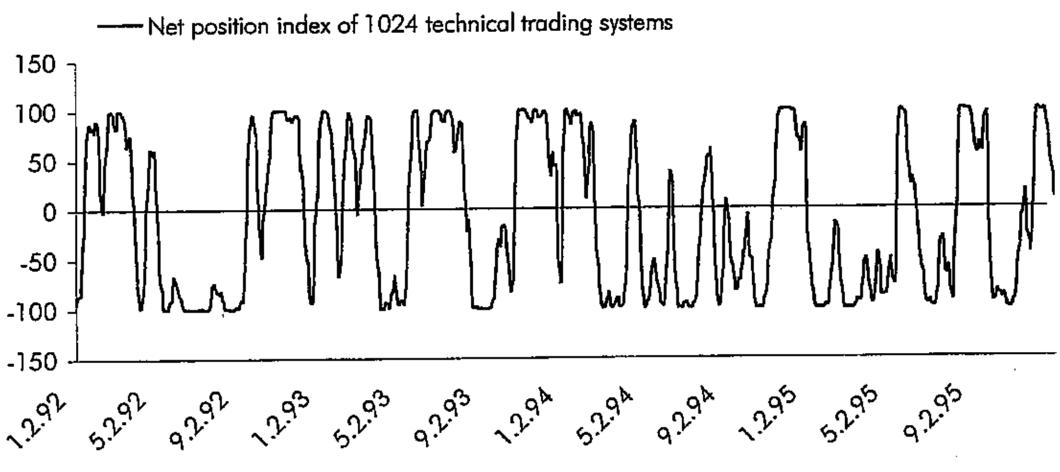
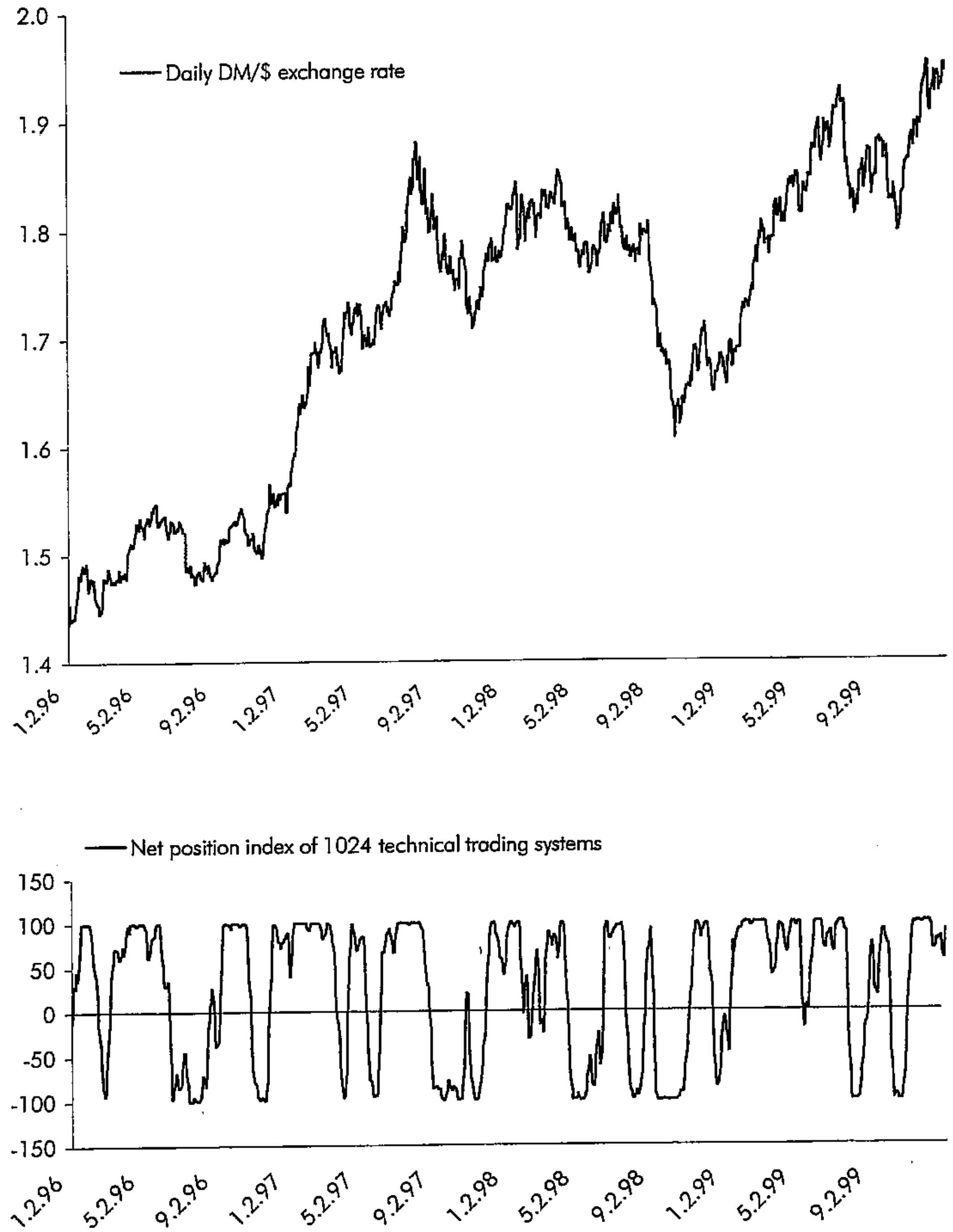


Figure 21a (cont.): Aggregate trading signals and exchange rate dynamics 1996-1999



The figures 20b and 21b show that the relationship between exchange rate movements and position switching on the part of the 1024 technical models for the yen/dollar market is very similar to the DM/dollar market.

Table 19a: Distribution of time by positions and transactions of technical trading systems Moving average and momentum models

DM/dollar-trading

	Aggregate positions			
Net position index	Share in total Sample period in %	Mean of the net position index	Mean of the gross position index	
			Long	Short
> 90	22.49	97.34	98.67	–1.33
70 - 90	9.77	81.22	90.61	–9.39
50 - 70	5.93	60.64	80.32	–19.68
30 - 50	4.05	40.03	70.02	–29.98
10 - 30	3.88	20.21	60.10	–39.90
–10 - 10	4.01	–0.42	49.79	–50.21
–30 - –10	3.92	–19.92	40.04	–59.96
–50 - –30	4.52	–40.60	29.70	–70.30
–70 - –50	5.87	–60.24	19.88	–80.12
–90 - –70	11.24	–81.18	9.41	–90.59
< –90	24.33	–97.48	1.26	–98.74
Total	100.00	–3.18	48.41	–51.59

	Aggregate transactions			
	Share in total Sample period in %	Mean of the net transaction index	Mean of the gross transaction index	
			Buy	Sell
> 70	0.00	0.00	0.00	0.00
50 - 70	0.13	54.43	55.69	–1.26
30 - 50	0.97	34.85	35.93	–1.08
10 - 30	12.67	17.26	19.04	–1.79
–10 - 10	72.33	0.01	3.37	–3.36
–30 - –10	12.87	–17.14	1.91	–19.05
–50 - –30	0.94	–36.11	1.23	–37.34
–70 - –50	0.07	–57.46	0.23	–57.70
< –70	0.01	–74.22	0.00	–74.22
Total	100.00	0.00	5.53	–5.53

Table 19a quantifies some of these observations. On 22.5% of all days of the entire sample period more than 95% of the models hold a long position (PI>90), and on 24.3% of all days more than 95% of the models hold a short position (PI<-90). Hence, on 46.8% of all days more than 95% of the models hold the same – long or short – position. 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 4.0% of all days. These situations occur primarily during the gradual 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).

On 72.3% of all days 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 exchange rate 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 (lasting for 20 trading days or more) 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 day: the transaction index lies between 10 and 30 (between –10 and –30) on 12.7% (12.9%) of all days. Only on roughly 2% of all days is technical trading more intense in the sense that more than 15% of the models execute trading signals.

Table 19a 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 10 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 3.4 which implies that only 1.7% of all models trade with each other on average).

Table 20a shows the similarity in the trading behavior of different classes of technical models. The position holding of stable models is more similar as compared to unstable models. E.g., more than 95% of the models hold the same – long or short – position on 53.4% of all days in the case of stable models but on only 47.5% in the case of unstable models. The similarity in the trading behavior increases with the duration of profitable positions, it is therefore highest for long-term models. The better is the performance of the models as measured by the t-statistic of the mean gross rate of return the more similar is the models' position holding. E.g., more than 95% of the models hold the same open position on 56.4% of all days in the case of the best performing models (t-statistic>4.0) as compared to 44.8% of all days in the case of the worst performing models (t-statistic<3.0).

The pattern of transactions and position holdings of the 1024 models is very similar when simulating yen/dollar trading as compared to DM/dollar trading (tables 19b and 20b).

Table 20a: Similarity of different types of technical trading systems in holding open positions

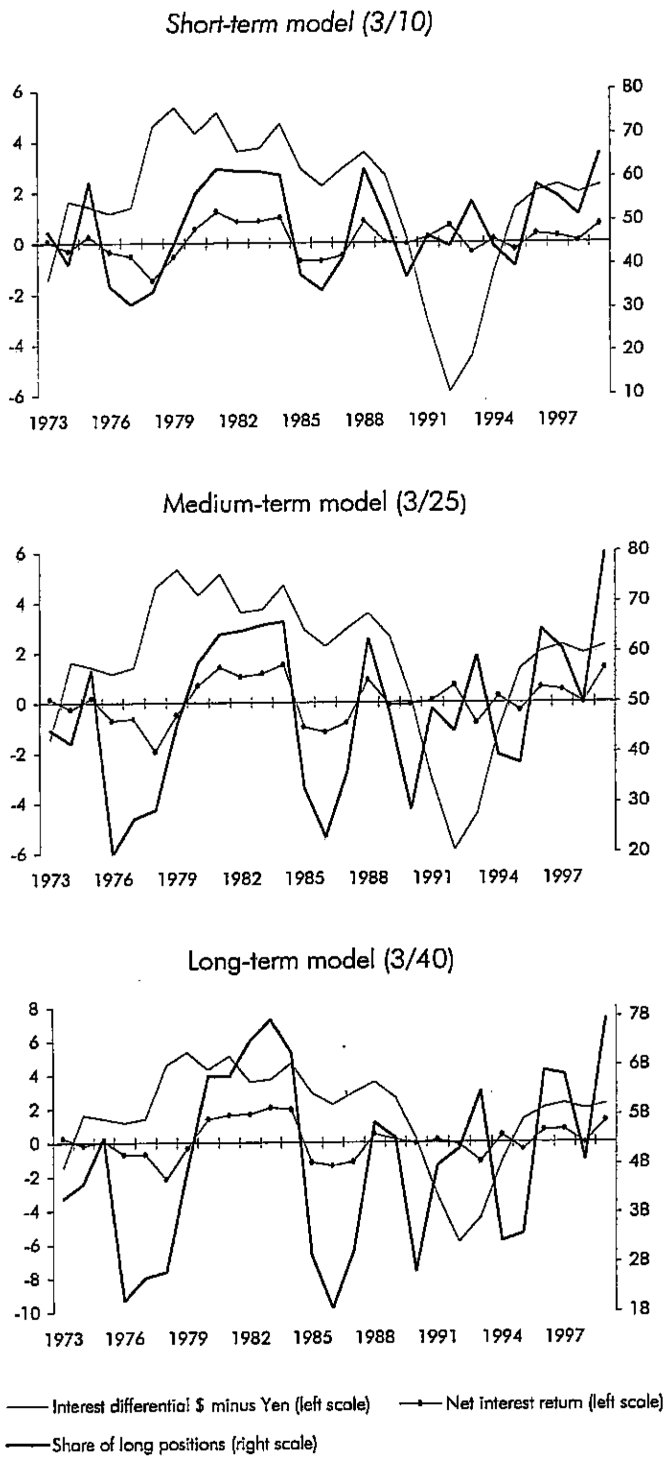
DM/dollar-trading

	Relative share of models holding the same – long or short – position				
	99% (|PI| > 98)	97.5% (|PI| > 95)	95% (|PI| > 90)	90% (|PI| > 80)	80% (|PI| > 60)
Types of models	Share in total sample period in %				
By stability					
Stable models	30.78	40.79	53.49	65.41	82.18
Unstable models	27.77	36.83	47.46	60.10	74.86
By duration of profitable positions					
Short-term	21.80	29.06	35.41	45.38	61.70
Medium-term	45.05	52.22	59.03	67.02	77.89
Long-term	65.49	72.06	76.21	80.82	87.05
By the t-statistic of the mean rate of return					
< 3.0	30.15	37.78	44.84	57.40	76.74
3.0 - < 3.5	26.17	36.99	48.37	62.38	81.29
3.5 - < 4.0	32.07	42.17	52.20	64.96	77.41
> 4.0	37.09	46.34	56.44	66.25	78.45
All models	27.21	36.17	46.82	59.37	74.16

5.3 The net interest return from technical currency trading

The effect of the differential between short-term dollar and short-term DM (yen) interest rates on the profitability of currency trading is estimated in the following way. Given the high similarity in position holding of technical models it is sufficient to select three moving average models (3/10, 3/25 and 3/40) as representative of short-term, medium term and long-term models. For every model and every year the relative share of long dollar positions is calculated (SPL= number of long positions*duration of long positions/365). On the assumption that the interest differential (IRD) is stable over each single year, the net interest return from currency trading (NIR) can be calculated as follows for each year: NIR = (2*SPL-1)*IRD.

Figure 22a: Net interest return from trading the moving average models in the DM/dollar market



The results are presented in figure 22a. In the years of an strong appreciating dollar (1980/84 and 1995/99) the net interest effect was positive since the duration of long positions was greater than that of short positions (the dollar interest rate was higher than the DM interest rate in all years besides 1973 and between 1991 and 1994). The opposite was true in the years of a depreciating dollar as between 1976 and 1979 and between 1985 and 1987. The total net interest return from following the three moving average models in the DM/dollar market over all 27 years is slightly positive (0.1% per year).

When the same models are used for trading the yen/dollar exchange rate between 1976 and 1979 the net interest return is somewhat higher (0.2% per year).

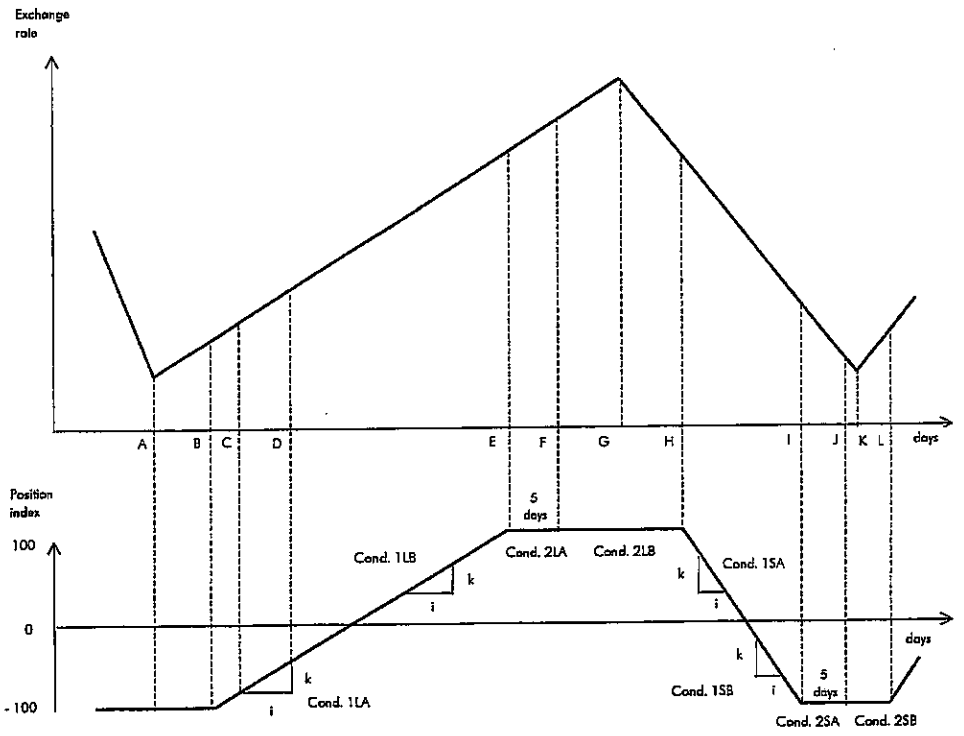
One can therefore conclude that accounting for the effect of the interest rate differential does not alter the results of this study concerning the profitability of technical currency trading.

5.4 The interaction between technical currency trading and exchange rate movements

As has been demonstrated, the profitability of technical currency trading stems exclusively from the exploitation of persistent trends around which the exchange rate fluctuates (these fluctuations are to a great extent filtered out by using moving averages or the first difference of prices for the generation of trading signals). 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 they hold 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 currency trading exerts an excess demand (supply) on exchange rate formation. It is therefore interesting to explore the interaction between the aggregate trading behavior of a great variety of different models and exchange rate dynamics. On one hand, technical models react to persistent appreciation (depreciation) movements by producing a series of buy (sell) signals, on the other hand, the execution of these signals strengthen and lengthen the exchange rate trend.

As a first step the possible interactions between the aggregate trading behavior of technical models and the development of an exchange rate trend shall be discussed in a stylized manner. Thereby an appreciation trend is taken as example and three phases of the trend are distinguished according to the positions held by technical models.

Figure 23: Exchange trends and aggregate positions of technical models



The first phase of an upward trend (marked by the days A and B in figure 23) must be caused by the excess demand of non-technical traders since most types of technical trading systems, in particular the two types tested in this study, are trend-following. In most cases this additional demand will be triggered off by some economic or political news (e.g., an unexpected high GDP growth of the U.S. economy) which let news-based traders expect an dollar appreciation and, hence, induce them to open (increase) long dollar positions.

Over the second phase of an appreciation trend (between day B and day E in figure 23) technical models produce a sequence of buy signals, the fastest models at first, the slowest models al 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 appreciation process going since there are many other traders whose aggregate transactions impact upon exchange rate movements. If, e.g., new information causes (most) news-based traders to switch their positions from long to short then this will turn the exchange rate movement from upward to downward (figure 21 demonstrates that the position index increases frequently over some days 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 appreciation movement (the reinforcing interaction between a rising dollar exchange rate and a rising share of technical models holding a long position is depicted in figure 21 by those situations where the position index increases gradually from -100 to +100).

Over the third phase of an appreciation trend all technical models hold long positions (marked by the days E and G in figure 23). In many cases the trend continues for some time during this phase (figure 21). 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 appreciation trend is caused by an additional demand of non-technical traders (however, the fact that all technical models hold a long position might foster the prolongation of the appreciation 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 appreciation movement the more the market "mood" is bullish on the dollar. 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., between 1980 and 1984 as well as between 1995 and 1999 the dollar exchange rate reacted much less to negative news like a higher than expected current account deficit as compared to positive news like a higher than expected growth in the U.S.

The longer an exchange rate trend 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 trend becomes progressively larger. Third, more and more 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 exchange rate trend finally comes to an end, mostly triggered off by some economic or political news, a countermovement is almost always triggered off (figure 21a). With some lag technical models start to close the former positions and open new counterpositions (on day H in figure 23).

For technical currency trading to be overall profitable it is necessary that appreciation (depreciation) trends continue for some time 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" exchange rate trend since they react to short-lasting countermovements. Third, slow models open a long (short) position only at a relatively late stage of an appreciation (depreciation) trend so that they can exploit the trend successfully only if it continues for some time.

In order to estimate how close exchange rate 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 exchange rate 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 12.5% (25%, 50%) of all models have been moving from short to long positions over the past 3 (5, 10) business days in such a way that the position index (PI) increases monotonically. In addition the condition 1L excludes all cases where more than 97.5% of the models hold long positions (these cases are comprised by condition 2L).

More formally condition 1L is defined as follows.

Condition 1L: $[PI_t - PI_{t-1}] > k \cap [PI_{t-n} - PI_{t-n-1}] \geq 0 \cap [PI_t \leq 95]$

k 25, 50, 100
i 3, 5, 10
n 0, 1, ... (i-1)

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

Condition 1S: $[PI_t - PI_{t-1}] < -k \cap [PI_{t-n} - PI_{t-n-1}] \leq 0 \cap [PI_t \geq -95]$

k 25, 50, 100
i 3, 5, 10
n 0, 1, ... (i-1)

Condition 2L(S) comprises all cases where more than 97.5% of all models hold long (short) positions:[13])

Condition 2L(S): PI > 95 (PI < 95)

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 day t on which these conditions are fulfilled the rate of change (CER_t) between the current exchange rate (ER_t) and the exchange rate j days (ER_{t+j}) ahead is calculated (j...5, 10, 20, 40). Then the means over the conditional exchange rate 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 the exchange rate continues to rise (fall) after 12.5% (25%, 50%) of technical

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[13]) 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 95 or lies below –95. These values were used instead of 100 and –100, respectively, for the following reason. This study includes also models with a difference in the length of the short-term and the long-term moving average of only one day. These models are extremely sensitive to exchange rate changes (the fastest produce 65 trading signals per year) and are therefore 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 days whereas all other models keep holding long (short) positions should still be considered typical of one-sided position holding of technical trading systems.

models have changed their position from short (long) to long (short), and if and to what extent this is the case when 97.5% of all models hold long (short) positions.

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

Table 21a shows that the conditions 1 are rather frequently fulfilled (DM/dollar trading). E.g., in 951 (953) cases more than 12.5% of all models change their open positions from short to long (from long to short) within 3 business days (conditions 1L(S) with k=25 and i=3, abbreviated as condition 1L(S)[25/3)]). In 693 (702) cases more than 25% of the models change their open position in the same direction within 10 business days. Conditions 1L(S)[100/10] are realized in only 406 (404) cases. The number of cases fulfilling conditions 1 are the smaller the larger is the parameter k. E.g., if k=100 then the possible realizations of condition 1L are restricted to a range of the position index between 50 and 95, however, if k=25 then condition 1L could be fulfilled within a range of the position index between 25 and 95.

Conditions 2 occur more frequently than conditions 1. In 1165 cases more than 97.5% of all models hold a long position (condition 2L). Since the dollar was depreciating over the entire sample period, condition 2S was even more frequently realized (1307 cases).

Despite the different restrictions imposed on conditions 1L(S) and 2L(S) either of them is fulfilled on 4376 days out of the entire sample of 6837 days (in order to avoid doublecounting only the cases of conditions 1L(S)[25/3] are considered as regards condition 1 – most cases satisfying condition 1 with k=50 or k=100 are a subset of the cases satisfying condition 1 with k=25). In the case of yen/dollar trading one of these four conditions is satisfied on 3933 days out of 6026 possible cases. Hence, the relative share of days on which one of the conditions 1L(S)[25/3] and 2L(S) hold true in the entire sample is almost the same for both currency markets (64.0% and 65.3%, respectively). This result implies a systematic pattern in the aggregate trading behavior of technical models which can hardly be reconciled with the assumption that the exchange rate follows a random walk.

Table 21a: Aggregate trading signals and exchange rate movements
All models

DM/dollar-trading

Parameters of the conditions for CER k	i	Time span j of CER	More than 12,5% (25%, 50%) of all models change open positions in the same direction within 3 (5, 10) business days: From short to long positions (condition 1L) Number of cases	Mean of CER_{t+j}	t-statistic	From long to short positions (condition 1S) Number of cases	Mean of CER_{t+j}	t-statistic
25	3	-3	951	0.8348	22.5197	953	–0.7929	–21.5368
		5	951	0.1447	3.5282	953	–0.2214	–3.8369
		10	951	0.2147	3.6650	953	–0.3444	–4.0473
		20	951	0.2870	3.2375	953	–0.3527	–2.2603
		40	951	0.1978	2.1306	953	–0.3564	–1.1707
50	5	-5	693	1.3973	27.5013	702	–1.2710	–25.5465
		5	693	0.1671	3.3424	702	–0.2957	–4.5434
		10	693	0.1867	2.7871	702	–0.3416	–3.4787
		20	693	0.3585	3.2637	702	–0.3721	–2.1370
		40	693	0.4080	2.9014	702	–0.3920	–1.1793
100	10	-10	406	2.5029	29.5368	404	–2.1973	–27.5090
		5	406	0.0120	0.5212	404	–0.2725	–3.1798
		10	406	–0.1556	–0.9085	404	–0.1891	–1.2459
		20	406	0.0229	0.6480	404	–0.2611	–1.0123
		40	406	0.1812	1.2831	404	–0.1681	–0.0382
			More than 97,5% of all models hold the same type of open position: Long positions (condition 2L)			Short positions (condition 2S)		
		5	1165	0.2565	5.9919	1307	–0.2428	–4.3066
		10	1165	0.4141	6.7894	1307	–0.4370	–5.3687
		20	1165	0.4714	5.7704	1307	–0.6908	–5.9649
		40	1165	0.5272	4.8342	1307	–0.9753	–5.8149

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

Condition 1L (S) comprises all situations where more than 12.5% (25%, 50%) of all trading systems have been moving monotonically from short to long (long to short) positions over the past 3 (5, 10) business days. The moves are restricted to a range of the position index PI_t between 95 and –95.

Condition 2L (S) comprises all situations beyond this range. i.e. where more than 97,5% of all trading systems hold long (short) positions.

More formally these conditions are defined as follows:

Condition 1L (S): $[PI_t - PI_{t-1}] > k\ (<-k) \cap [PI_{t-n} - PI_{t-n-1}] \geq 0 \leq = 0 \cap [-95 \leq PI_t \leq 95]$
k……25, 50, 100
i……..3, 5, 10
n…….0, 1, … t_{i-1}

Condition 2L (S): PI > 95 (< -95)

$CER_{t+j} = 100 * [ER_{t+j} - ER_t] / ER_t$ for j……..5, 10, 20, 40
$CER_{t+j} = 100 * [ER_t - ER_{t+j}] / ER_t$ 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 -0.0160 (1.1672)
5 -0.0266 (1.5199)
10 -0.0518 (2.2033)
20 -0.0948 (3.2471)
40 -0.1581 (4.7180)

The means of the exchange rate changes (CER_t) on all days satisfying condition 1 over the past 3 (5,10) days are very much higher than the unconditional means over the entire sample period (at the same time the exchange rate moves in the same direction as the position index). E.g., the average (relative) exchange rate change over 5 consecutive days amounts to –0.027% between 1973 and 1999, however, when 25% of the technical models turn their open position from short to long within 5 days the exchange rate increases on average by 1.40%. This highly significant difference (t-statistic: 27.5) can be explained as the result of the interaction between exchange rate movements and the (thereby induced) changes of open positions by technical models.

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 currency markets, two observations can be made with respect to the simultaneous exchange rate changes (see all lines in the tables 21a/b to 24a/b where the time span j of CER_t is negative). First, the exchange rate moves on average strongly in the direction congruent with the simultaneous transactions of technical currency trading. Second, the means of the conditional (ex-post) exchange rate changes differ significantly from the unconditional means (the t-statistics exceed 20 in most cases). However, since exchange rate movements and technical position taking interact simultaneously one cannot separate that part of the (ex-post) conditional exchange rate 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 the exchange rate changes over the 5 (10, 20, 40) days following the realization of condition 1 has mostly the same sign as the preceding change in the position index (tables 21a and 21b). This holds true in all cases of changing positions from long to short induced by and strengthening the depreciation movements (conditions 1S). In only 5 out of 24 cases the exchange rate falls on average subsequent to realizations of condition 1, i.e., after a certain share of models has changed positions from short to long. In 3 of these cases (concerning the yen/dollar market – table 21b) the means of the conditional ex-ante exchange rate changes are still significantly greater than the unconditional means (the yen depreciates in these cases less than on average over the entire sample period).

The means of the conditional ex-ante exchange rate changes are in most cases significantly different from the unconditional means albeit to a lesser extent than the means of the conditional ex-post exchange rate changes (the t-statistics testing the significance of the difference between the means of the conditional ex-ante exchange rates and the unconditional means exceed 2.0 in most cases – table 21a). The main reason for why the means of the conditional exchange rate changes are smaller in the case of ex-ante changes as compared to ex-post changes is due to the fact that exchange rate trends often reverse their direction before or shortly after all technical models have changed their position.

However, exchange rate trends continue sufficiently often for several weeks after conditions 1 are fulfilled so that the conditional means of the ex-ante exchange rate changes are significantly higher (in absolute terms) than the unconditional means over the entire sample period. Only for exchange rate changes (over all four time spans) subsequent to the realizations of condition 1L(S)[100/10] does this not hold true in the case of the DM/dollar market. The reason for this exception might be as follows. The condition 1L(S)[100/10] excludes all cases where the position index changes by less than 100 index points (in absolute terms). At the same time the exchange rate changes following these cases are often strong and persistent as implied by the high means of the ex-ante exchange rate changes (in absolute terms) under the conditions 1L(S)[25/3] and 1L(S)[50/5].

After those days on which 97.5% of all models hold a long (short) position (condition 2) the exchange rate rises (falls) much stronger than on average over the entire sample (tables 21a and 21b). The means of the conditional (ex-ante) exchange rate changes are even more significantly different from the unconditional means than in the case of conditions 1. This implies that the probability of a prolongation of an exchange rate trend is higher after (almost) all models have opened the same – long or short – position as compared to those phases where the models are still changing their positions from short to long or vice versa. The frequent continuation of exchange rate trends after conditions 2 are satisfied must be attributed primarily to the transactions of non-technical traders since 97.5% of all models used in this study are just keeping their positions (as has already been discussed it seems rather unprobable that models which produce less trades than the slowest models of this study are used in practice).

Table 22a: Aggregate trading signals produced by different types of technical models and exchange rate movements

DM/dollar-trading

Types of models	Time span j of CER_{t+j}	More than 25% of all models change open positions in the same direction within 5 business days (K = 50, i = 5, –95 ≥ PI ≤ 95)					
		From short to long positions (condition 1L)			From long to short positions (condition 1S)		
		Number of cases	Mean of CER_{t+j}	t-statistic	Number of cases	Mean of CER_{t+j}	t-statistic
Stable	-5	465	1.3541	20.1503	441	–1.2849	–19.3446
	10	465	0.0430	0.8703	441	–0.3480	–2.8527
	20	465	0.3151	2.4204	441	–0.4198	–2.1107
Unstable	-5	775	1.2934	26.5465	757	–1.2024	–24.7201
	10	775	0.2184	3.4061	757	–0.3969	–4.3097
	20	775	0.3264	3.2691	757	–0.4103	–2.5021
Short-term	-5	1132	1.2954	36.2104	1120	–1.2443	–32.9071
	10	1132	0.1956	3.5924	1120	–0.2792	–3.2694
	20	1132	0.2253	3.0785	1120	–0.2755	–1.6931
Medium-term	-5	774	1.2188	24.6088	786	–1.0471	–21.1374
	10	774	0.1932	3.0694	786	–0.3337	–3.4588
	20	774	0.2201	2.4457	786	–0.2491	–1.2210
Long-term	-5	494	1.0964	17.5983	493	–1.0611	–16.6847
	10	494	0.0130	0.6137	493	–0.3394	–2.9048
	20	494	0.2949	2.4065	493	–0.4121	–2.1782
		More than 97.5% of all models hold the same type of open position					
		Long positions (condition 2L: PI > 95)			Short positions (condition 2S: PI < –95)		
		Number of cases	Mean of CER_{t+j}	t-statistic	Number of cases	Mean of CER_{t+j}	t-statistic
Stable	10	1331	0.3566	6.2842	1457	–0.4352	–5.5852
	20	1331	0.3736	4.9949	1457	–0.6489	–5.7648
Unstable	10	1192	0.4103	6.7342	1325	–0.4167	–5.1878
	20	1192	0.4698	5.6884	1325	–0.6776	–5.9163
Short-term	10	967	0.4681	6.5878	1019	–0.4348	–4.8418
	20	967	0.6006	6.1551	1019	–0.6586	–4.9733
Medium-term	10	1716	0.2836	5.7267	1854	–0.3783	–5.3690
	20	1716	0.3560	5.2484	1854	–0.5593	–5.4855
Long-term	10	2343	0.2155	5.1611	2582	–0.3241	–5.2093
	20	2343	0.2288	4.2789	2582	–0.4937	–5.3781

For a definition of the conditions 1L (S) and for the conditions 2L (S) see Table 21a.

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 -0.0266 (1.5199)
10 -0.0518 (2.2033)
20 -0.0948 (3.2471)

Table 23a: Aggregate trading signals produced by different types of technical models and exchange rate movements

DM/dollar-trading

Types of models by the t-statistic	Time span j of CER_{t+j}	More than 25% of all models change open positions in the same direction within 5 business days ($K = 50$, $i = 5$, $-95 \geq PI \leq 95$)					
		From short to long positions (condition 1L)			From long to short positions (condition 1S)		
		Number of cases	Mean of CER_{t+j}	t-statistic	Number of cases	Mean of CER_{t+j}	t-statistic
< 3.0	-5	565	0.7639	12.7787	561	–0.6744	–10.9758
	10	565	–0.0468	0.0533	561	–0.0787	–0.2796
	20	565	0.0122	0.7205	561	–0.1358	–0.2798
3.0 - < 3.5	-5	442	1.1127	16.8565	428	–1.0227	–15.0712
	10	442	0.0297	0.7438	428	–0.2716	–2.0385
	20	442	0.2095	1.7549	428	–0.3467	–1.5484
3.5 - < 4.0	-5	648	1.2742	23.6711	677	–1.0895	–21.0749
	10	648	0.2788	3.8527	677	–0.2755	–2.6746
	20	648	0.3651	3.2324	677	–0.2439	–1.1307
> 4.0	-5	664	1.3824	29.7421	676	–1.3206	–29.4462
	10	664	0.3091	4.3771	676	–0.2277	–2.0501
	20	664	0.2582	2.6558	676	–0.2198	–0.9337
		More than 97.5% of all models hold the same type of open positions					
		Long positions (condition 2L: PI > 95)			Short positions (condition 2S: PI < –95)		
		Number of cases	Mean of CER_{t+j} Long position	t-statistic	Number of cases	Mean of CER_{t+j} Short position	t-statistic
< 3.0	10	1211	0.3871	6.5739	1371	–0.3750	–4.5707
	20	1211	0.4507	5.6300	1371	–0.5626	–4.7946
3.0 - < 3.5	10	1190	0.4053	6.6912	1338	–0.4202	–5.1814
	20	1190	0.4565	5.6162	1338	–0.6435	–5.4859
3.5 - < 4.0	10	1375	0.3614	6.3543	1507	–0.3844	–5.0231
	20	1375	0.4104	5.3889	1507	–0.6693	–6.1509
> 4.0	10	1530	0.3406	6.3087	1638	–0.4306	–5.9276
	20	1530	0.4293	5.7128	1638	–0.6434	–6.0398

For a definition of the conditions 1L(S) and the conditions 2L(S) see Table 21a.

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 -0.0266 (1.5199)
10 -0.0518 (2.2033)
20 -0.0948 (3.2471)

Table 24a: Eight phases of technical trading and exchange rate movements
All models

DM/dollar-trading

Conditions for CER_{t+i} (= Phases of technical trading)	Time span i of CER_{t+i}	(Increasing) Long positions (conditions .L.)			(Increasing) Short positions (conditions .S.)		
		Number of cases	Mean of CER_{t+i}	t-statistic	Number of cases	Mean of CER_{t+i}	t-statistic
1A	-5	174	1.5226	17.4593	520	−1.2273	−17.0317
	5	174	0.2282	2.1356	520	−0.3395	−4.5745
1B	-5	519	1.3553	23.8193	182	−1.3958	−16.0356
	5	519	0.1467	2.6847	182	−0.1705	−1.3130
2A	5	869	0.3083	6.5853	977	−0.2296	−3.7636
2B	5	296	0.1044	1.2951	330	−0.2818	−2.3237
1A	10	174	0.1570	1.3183	520	−0.3335	−2.9125
1B	10	519	0.1967	2.5134	182	−0.3648	−2.0661
2A	10	869	0.4823	6.7675	977	−0.4285	−4.8477
2B	10	296	0.2141	2.1740	330	−0.4620	−2.6656
1A	20	174	0.2474	1.2738	520	−0.4721	−2.6038
1B	20	519	0.3958	3.0854	182	−0.0862	0.0325
2A	20	869	0.6726	6.8365	977	−0.7247	−5.6871
2B	20	296	−0.1193	−0.1414	330	−0.5905	−2.4779
1A	40	174	0.2818	1.1440	520	−0.4319	−1.2025
1B	40	519	0.4503	2.7443	182	−0.2778	−0.3153
2A	40	869	0.7249	5.3341	977	−1.0144	−5.2375
2B	40	296	−0.0533	0.4483	330	−0.8594	−2.9543

Each of the four phases of technical trading defined by the conditions 1L (S) and the conditions 2L (S) for k = 50 and i = 5 (see Table 21) is divided into two subphases by the conditions A and B:

Condition 1L (S): More than 25% of all trading systems have been moving from short to long (long to short) positions over the past five business days within the range $\{-95 \leq PI_t \leq 95\}$ 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 hold long (short) positions, i.e. $PI_t \geq 0$ ($PI_t \leq 0$).

Condition 2L (S): More than 97.5% of all trading systems hold long (short) positions, i.e. $PI_t > 95$ ($PI_t < 95$).

Condition 2L (S) A: Comprises the first five business days for which condition 2L (S) holds true.

Condition 2L (S) B: Comprises the other days for which condition 2L (S) holds true.

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 -0.0266 (1.5199)
10 -0.0518 (2.2033)
20 -0.0948 (3.2471)
40 -0.1581 (4.7180)

The tables 22a/b and 23a/b present the results of the statistical analysis of the relationship between the trading behavior of different classes of technical models according to the conditions 1 and 2 and the exchange rate movements before and after the realizations of both conditions. The models are classified according to their stability, the average duration of their profitable positions as well as their performance as measured by the t-statistic of the means of their single returns. Condition 1 is used only with k=50 and i=5, the ex-ante exchange rate changes are restricted to a time span of 10 days and 20 days, respectively. The main results do not differ from those obtained for all 1024 models (table 21a and 21b). However, the following additional observations are worth mentioning.

First, stable models (i.e., models which produce positive returns over each subperiod) realize condition 1 25% of all models change their open position in the same direction within 5 days less frequently than unstable models. Second, stable models are more frequently on the same side of the market (condition 2) as compared to unstable models. Both observations are explained by the fact that unstable models react in general faster to exchange rate changes as compared to stable models. Third, for a similar reason short-term models realize condition 1 more frequently than medium-term models. Condition 1 is least frequently realized by long-term models, e.g., on only 494 (493) days out of 6837 possible cases (entire sample size) more than 25% of the long-term models change open positions from short to long (long to short) within 5 days in the DM/dollar market (table 22a). Fourth, since long-term models trade relatively seldom they realize condition 2 much more frequently than short-term models. In the DM/dollar market, e.g., 97.5% of all models hold the same – long or short – position in 4925 out of 6837 possible cases. By contrast, 97.5% of the short-term models are on the same side of the market on only 1986 days. Fifth, the means of the ex-ante exchange rate changes under condition 2 are significantly different from the unconditional means in all cases.

If one classifies the models according to their performance as measured by the t-statistic of the mean of the single returns, the following observations are of interest (tables 23a and 23b). The two classes of best performing models (with a t-statistic greater than 4.0 or between 3.5 and 4.0) realize conditions 1 and conditions 2 more frequently than the two worse performing classes of models with a t-statistic smaller than 3.5 (however, this does not hold true with respect to the conditions 1 in the case of the yen/dollar market). At the same time the means of the conditional ex-ante exchange rate changes are always significantly higher (in absolute terms) than the unconditional means in the case of the two classes of best performing models.

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=50 and i=5). The meaning of the (sub)conditions A and B is explained as follows, taking an appreciation trend as example.

Condition 1LA comprises all cases where 25% 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 exchange rate has started to rise (all cases under condition 1LA lie below the zero level of the position index – see figure 23).

Condition 1LB comprises the second phase of position changes, i.e., when the exchange rate trend 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 business days after more than 97.5% of all models have opened long positions.

Condition 2LB comprises the other days over which 97.5% 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 an depreciation movement.

Figure 23 illustrates the meaning of these eight conditions which correspond to eight (stylized) phases of technical trading (whenever exchange rate movements develop to persistent upward and downward trends).

Table 24a shows that the size of the conditional ex-ante exchange rate changes differs strongly and systematically across the four conditions 1LA, 1LB, 2LA and 2LB (i.e., in the case of an upward trend). The average rise of the DM/dollar exchange rate following the realizations of condition 1LA, is relatively low, it gets higher after the exchange rate trend has gained momentum (condition 1LB) and reaches its maximum following the realizations of condition 2LA (which are restricted to the first 5 days after 97.5% of all models have taken long positions). Exchange rate changes subsequent to the realizations of condition 2LB are smallest and sometimes even negative (the exchange rate changes between day (t) and day (t+10) or (t+20) will often be negative if day (t) belongs to the last phase of an upward trend – see figure 23). As a consequence, the means of the conditional ex-ante exchange rate changes differ most significantly from the unconditional means in the cases of condition 1LB and condition 2LA. This result also holds true for the conditional ex-ante exchange rate changes in the yen/dollar market (table 24b).

When looking at the four phases of technical trading related to depreciation movements the results are different in two respects (tables 24a and 24b). First, the means of the conditional ex-ante exchange rate changes differ more significantly from the unconditional means in the case of condition 1SA as compared to condition 1SB. Second, subsequent to the realizations of condition 2SB the exchange rate changes to a larger extent on average than in the case of condition 2LB. In addition, the means of the conditional ex-ante exchange rate changes (condition 2SB) are always negative (i.e., in line with the prevailing downward trend) and in most cases significantly different from the unconditional mean over the entire sample. These two differences in the conditional ex-ante exchange rate changes between appreciation and depreciation trends might be due to the fact that downward movements are on average steeper and longer lasting than upward movements in both markets (the dollar depreciated over the entire sample periods against both currencies, the DM and the yen).

The three most important observations concerning the interaction between exchange rate 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) the exchange rate moves in the direction congruent with the transactions of the technical models. At the same time the means of these conditional ex-post exchange rate changes are very much higher than on average over the entire sample period. This observation reflects the strong and simultaneous feedback between exchange rate movements and the transactions triggered off by technical models. Second, the means of exchange rate changes taking place over 5 (10, 20, 40) days after a certain part of technical models has reversed the open positions at a certain speed (according to condition 1) have almost always the same sign as the preceding change in the position index and are in most cases significantly higher than the unconditional means over the entire sample period. Third, this holds also (and even to a higher extent) true for exchange rate changes following all days when 97.5% of the models hold the same – long or short – position.

The last two observations reflect the finding of this study that all tested technical models produce excess returns over the entire sample period due to profitable positions lasting longer than unprofitable positions. One can therefore conclude that the frequent occurrence of persistent exchange rate trends accounts for two important results of this study. First, exchange rate trends exclusively account for the overall profitability of each of the 1024 technical models in both currency markets. Second, exchange rate trends last sufficiently often so long that (almost) all 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 exchange rate trends and the related aggregate trading behavior of technical models. First, exchange rate 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" in favor or against the dollar causing medium-term exchange rate expectations to be biased upward or downward. If, e.g., the market is "bullish" on the dollar new-based traders will react much stronger to news which confirm the expectation of a rising dollar exchange rate than to news which contradict this expectation. In addition, all types of traders might in this case put more money into a long dollar position than into a short position (and vice versa if the market is "bearish" on the dollar). Third, non-technical "bandwagonists" join the exchange rate 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 currency trading, namely, that the exchange rate continues 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".

6. Summary and evaluation of the results

In this final section, the main results of the study will be summarized. This section will also evaluate these results 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 unstabilizing speculation and profitable versus unprofitable speculation. The main conclusion is that financial markets are inherently unstable and technical trading can be considered a rational adaptation to the inherent instability.

6.1 The main results of the study

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

- Each of the 1024 moving average and momentum models investigated produced a positive overall return when trading the daily DM/dollar exchange rate as well as the daily yen/dollar exchange rate over the entire sample period (1973/99 and 1976/99, respectively).

- 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 2.5 in almost all cases).

- The profitability of technical currency trading is exclusively due to the exploitation of persistent exchange rate trends around which the daily rates 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 day during unprofitable positions is higher then the average profit per day during profitable positions.

- These results do not change substantially when technical currency is simulated over 7 subperiods for DM/dollar trading (6 subperiods for yen/dollar trading). In only 755 out of 7168 cases (performance of 1024 models over 7 subperiods in the DM/dollar market) and in only 271 out of 6144 cases (yen/dollar market) did the technical models produce losses. However, the profitability of technical currency trading based on daily data has been declining over the entire sample period in both markets, the DM/dollar as well as the yen/dollar market.

- The out-of-sample ex-ante profitability of those models which performed best in sample (i.e., over the most recent subperiod and over all past subperiods, respectively) is slightly higher than the average in-sample ex-post profitability of all models. (There was only one subperiod in which the best models in sample made losses out of sample). However, the ex-post best models perform much worse out of sample than in sample. This difference is mainly due to a "model mining" bias.

- If one aggregates the transactions as well as open positions from all of the 1024 technical models, it turns out that they exert an excessive demand (supply) pressure on currency markets. This is so for two reasons. First, when technical models produce trading signals they are either buying or selling (i.e., technical models using the same frequency of price data do not trade with each other). Second, when technical models maintain open positions almost all of them are on the same side of the market, either long or short.

- There is a strong feed-back mechanism operating between exchange rate movements and the transactions triggered off by technical models. A rising exchange rate, for example, causes increasingly more technical models to produce buy signals, which in turn strengthen and lengthen the appreciation trend.

- After a certain proportion of technical models has changed their open positions from short to long (long to short) the exchange rate continues to rise (fall) over the subsequent days or even weeks. This holds to a higher extent true after almost all technical models have taken long (short) positions.

6.2 Technical analysis and the efficient market hypothesis

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. Exchange rates, for example, are determined by the transactions of rational market agents in such a way that they equalize the purchasing power of different currencies (PPP condition) and their respective yields (uncovered interest parity condition). If one allows for different preferences of the respective countries concerning their net external asset position then the exchange rate might deviate in equilibrium from purchasing power parity as in the case of "real equilibrium exchange rate" models (MacDonald-Stein, 1999). Whatever the true model of an asset price like the exchange rate might be it is always assumed that rational market agents know its fundamental equilibrium and drive the market price instantaneously to its new fundamental level if the latter changes due to new information. 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 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 currency trading was consistently profitable in both markets, the DM/dollar as well as the yen/dollar 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).

6.3 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). Since noise traders are defined as all kinds of non-fundamentalist traders they comprise very different types of market participants like people whose transactions depend to a large extent on their emotions, 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.[14])

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, the market rewards bearing a higher risk (due to the activity of noise traders) through higher (expected) returns. Any positive return noise traders might earn only compensates them for bearing higher risk (without being aware of it). Seventh, 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 to a very common type of noise trading, i.e., technical trading. First, the high returns of technical trading in sample and out of sample together with the extremely 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 over the long run (the sample period of this study covers 27 and 24 years, respectively). 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 moving average models and momentum models is much less unpredictable than

[14]) 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, 1998.

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. Fourth, the information used by technical models and the way these models process this data to derive trading signals does not seem as useless as asserted by the noise trader approach. This statement concerns not so much the informational content of the most recent price moves but rather the "theoretical" essence of technical analysis, namely the perception of asset price dynamics as a sequence of upward and downward trends, sometimes interrupted by "whipsaws".

The last point deserves additional discussion, taking as an example the specific form of expectations formation implied by the use of technical models. By following technical models traders (implicitly) form price expectations only in a qualitative manner, i.e., 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 "bull markets" and "bear markets" 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 (fundamentalists as well as noise 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.

This example shows that the noise trader approach rather arbitrarily assumes that only fundamentalists are smart traders whereas the trading of all other agents – including technical traders – is based on useless information. Two conclusions are derived from this assumption. First, any non-fundamentalist trading cannot be profitable in excess of the higher risk caused by noise trading itself (the only exception being the bandwagon trading of otherwise fundamentalist traders when exploiting the noise traders). Second, in the long run, prices return to fundamental values, however, at short horizons they move in a bubble-like pattern (due to the interaction of rational and noise traders).

Now, if prices move in a bubble-like pattern, then one should allow for the possibility that such a pattern might be profitably exploited. The types of traders who try to separate the systematic components of price movements (underlying trends) from short-term fluctuations are of course the technical traders. Since technical trading can and often will be profitable, it should be considered a rational, non-fundamental and consequently destabilizing form of speculation (in the following, the term "noise traders" refers therefore to all agents who are neither fundamentalist nor technical traders).

If price trends can be profitably exploited by means of technical analysis then the system of asset price determination as a whole might change 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 last section sketches hypothetically how technical traders might interact with other types of traders under this condition.

6.4 Technical analysis and the financial instability hypothesis

The financial instability hypothesis, in the spirit of Keynes (1936), Minsky (1982) and Kindleberger (1996), holds that financial markets are inherently unstable, overshooting is not an anomaly, but an essential element of price dynamics and fundamental equilibrium serves at best as some kind of attractor around which prices fluctuate widely and persistently (phases of an overvaluation or undervaluation of an asset can last for several years).

There are at least four reasons for the systemic instability of financial markets. First, most trading is motivated by the attempt to profit from the difference between present and future prices. However, since the future is inherently uncertain, the logic of arbitrage as trading in space does not apply to speculation as trading in time (arbitrage will always narrow price differences in space, however, speculation can and often will increase price differences in time). Second, economic agents are human beings and therefore are driven by rationality and emotions. Third, the excitement of individuals and groups is particularly pronounced as far as quick profits or losses in "money games" are concerned. Fourth, these emotions are "bundled" through world-wide information networks and manifest themselves as market "moods" such as euphoria or (sometimes) panics, causing herd effects over time and across market places.

According to the financial instability hypothesis, the pattern of speculative prices is the outcome of the interaction of different trading strategies, namely, news-based trading, technical trading, noise trading, contrarian trading and fundamentals-oriented trading.

Price runs are triggered off by some economic or political news if a sufficient number of traders believe that this (unexpected) information will cause other traders to open a new position in the market. Since the expectation about other agents' expectations (Keynes' "beauty contest" problem) has to be formed within seconds, news-based traders will not try to gauge the new price level to prevail in the (near) future, but will form only qualitative expectations about the directions of imminent price movements (a correct directional expectation is sufficient for a "round-trip" trade to make a profit)[15]).

Once a price run has gained some momentum, other traders who base their trading decisions on trend-following technical systems take the same (long or short) position, thereby strengthening the run (technical trading signals also imply only directional price expectations). Noise traders, in particular amateur speculators (the "doctors and dentists") who usually jump on the bandwagon later than professional traders then extend the price trend even further.

The longer an upward (downward) trend lasts, the fewer buy (sell) orders are generated by technical traders and (amateur) "bandwaggonists" and the trend loses momentum. In such a situation, contrarian traders jump in, hoping to profit from an imminent reversal of the trend (thereby contributing to such a reversal). In addition, transactions which cash in the profit from exploiting a price trend occur more frequently the longer a trend lasts.

Hence, the interaction between contrarian trading and cash-in transactions brings any short- and medium-term trend to an end, thereby often initiating a new trend in the opposite direction.

Price runs in one direction can occur more frequently than runs in the other direction over long periods of time, in some cases lasting years, because there often prevails an expectational bias in favor or against a certain asset (e.g., a bias in favor of the dollar prevailed 1980/85 and 1995/2000). If a current run is in line with the bias, traders put more money into an open position and/or hold such a position longer than in the case of a run against the bias (overnight positions in line with the "bullish" or "bearish" sentiment of the market are known as "strategic positions").

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[15]) The term "news-based trading" as used in this study describes a behavior different from fundamental trading in the sense of equlibrium economics for the following reason. Even if a piece of new information concerns market fundamentals a news-based trader will use it only as a signal which might strenghten or reverse the directional expectations of other news-based traders. Hence, the news are not used to (re)estimate the fundamental equilibrium value according to the "true" asset pricing model.

But the more an asset becomes over(under)valued during a bull (bear) market, the more it sews the seeds of its own destruction, as news hits the market indicating a change in the long-term trend. This is a consequence of the impact of price overshooting on the real sphere of the economy. In the case of exchange rates, e.g., any persistent overvaluation will "ceteris paribus" dampen the growth of exports and production and will deteriorate the current account.

In such a situation, those fundamentals-oriented traders who base their expectations on the discrepancy between the current price and its fundamental value, open (often huge) positions against the "out-fading" trend (the most famous single speculator who followed such a strategy was George Soros - a diary of his transactions can be found in Soros, 1987).[16])

Even though the financial instability hypothesis sketches a picture of trading behavior and price dynamics in financial markets radically different from the perception of equilibrium economics, it takes into account many of the real-world features of the market place. This concerns in particular the widespread use of technical trading systems. This study has attempted to provide evidence on the rationale for this kind of trading behavior and on its destabilizing effects on asset prices.

[16]) The behavior of fundamentals-oriented traders differ from fundamentalist trading in two respects. First, fundamentals-oriented traders keep holding open positions when an asset price moves away from the fundamental equlibrium as long as they believe that the "bullish" or "bearish" market forces are still "alive". Second, after the trend has reversed its direction they do not close out their (new) open position when the fundamental price level is reached but keep "riding the trend".

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