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PROFITABILITY AND PRICE EFFECTS OF TECHNICAL CURRENCY TRADING

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Abstract

The study investigates profitability and price effects of 1024 moving average and momentum models in the DM/dollar market (1973/99) as well as in the yen/dollar market (1976/99). The main results are as follows. First, each of these models would have produced an positive return over the entire sample period. The probability of making an overall loss when strictly following one of these models would have been close to zero. Second, this profitability is exclusively due to the exploitation of persistent exchange rate trends around which the daily rates fluctuate. Third, these results do not change substantially when technical currency is simulated over subperiods. Fourth, the out-of-sample profitability of those models which performed best in sample (i.e., over the most recent subperiod) is slightly higher than the average in-sample profitability of all models. However, the ex-post best models perform much worse out of sample than in sample. Fifth, the aggregate transactions and positions of technical models exert an excessive demand (supply) pressure on currency markets. Sixth, 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.

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PROFITABILITY AND PRICE EFFECTS OF TECHNICAL CURRENCY TRADING

1. Introduction

Trading techniques based on the so-called technical analysis are widely used in financial markets. This is particularly true for the currency markets (Group of Thirty, 1985; Taylor-Allen, 1992; Menkoff, 1998; Wolgast, 1997; Lui-Mole, 1998; Cheung-Wong, 2000).

Hence, an increasing number of studies has recently investigated the profitability of technical trading rules in the foreign exchange market as well as in the stock market (see, e.g., Schulmeister, 1987, 1988; Levich-Thomas, 1993; Menkhoff-Schlumberger, 1995; Goldberg-Schulmeister, 1988; Schulmeister-Goldberg, 1989; Brock-Lakonishok-LeBaron, 1992; Chang-Osler, 1999; Osler, 2000; Lo-Mamaysky-Wang, 2000).

Most 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 post profitable trading rules which a trader in practice would not be able to choose ex ante (Sullivan-Timmermann-White, 1999).

There is one issue which is important for a better understanding of the dynamics of financial markets, irrespective of whether technical trading is excessively profitable or not. This concerns the impact of the use of technical systems on price fluctuations. This influence has not yet been empirically investigated (for theoretical treatments see Cutler-Poterba-Summers, 1991; De Long-Shleifer-Summers-Waldmann, 1990A and B; Frankel-Froot, 1990). It is the main scope of this study to shed some light on this issue.

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The paper summarizes the most important results concerning profitability and price effects of technical trading in the DM/$ market (1973-1999) as well as in the yen/$ market (1976-1999) elaborated in a more comprehensive study (Schulmeister, 2000). The results presented in the tables and figures of this paper refer only to DM/$ trading. This restriction is chosen for three reasons. First, the results of simulating yen/$ trading differ very little from those obtained for DM/$ trading (any significant difference will be commented in the main text). Second, readers interested in details concerning technical trading in the yen/$ market might consult the original study (Schulmeister, 2000). Third, the paper shall be kept as short as possible.

The first part of the paper summarizes the (ex-post) profitability of 1024 technical models over the entire sample period as well as their performance in sample and out of sample over different subperiods.

The second part investigates the impact of the use of many different trading models upon exchange rate dynamics. In a first step indices of the aggregate transactions and open positions of the 1024 technical models are calculated for any point in time. Based on these indices the concentration of transactions on buys or sells, and of position holdings on long or short is documented. Finally, the relationship between the level and the change of the net position index and subsequent exchange rate movements is analyzed.

2. The performance of technical currency trading

2.1 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 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).

The qualitative approaches rely on the interpretation of some (purportedly) typical configurations of the ups and downs of price movements and 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. 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.

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.

There exist many modifications of the basic version of moving average and momentum models (see, e.g., Kaufman, 1987, chapters 5 and 6). This study, however, 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".

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).

2.2 The profitability of technical trading systems and its components over the entire sample period

The simulations comprise the following models. 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 (474 models). In the case of momentum models the time span i runs from 3 to 40 days (38 models). [1])

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.

2.2.1 Overview of the performance of 1024 trading systems

Table 1 shows the performance of three moving average and three momentum models over the entire sample period. The selection comprises models which are very different with respect to their

[1]) The main criterion for the selection of the parameter ranges was to cover those models that are actually used by professional traders. Even though dealers revealed in 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) have not been tested because those extremely slow models are not used in practice (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).

price sensitivity. The fastest models operating with relatively short moving averages or time spans in the case of momentum models display an average duration of profitable positions between 20 and 30 days (they focus on the exploitation of short-term exchange rate trends like the moving average model 1/16 or the momentum model 9). Most of the selected models display an average duration of profitable positions between 30 and 60 days, only the moving average model 11/30 specializes on the exploitation of long-term exchange rate trends.

All of the selected models are profitable, their gross rates of return center around 10% per year. The net rate of return is only slightly smaller given the low transactions costs in the competitive foreign exchange market (Schulmeister, 2000).

For any open position interest is earned from the long position and paid for the short position. Thus, the overall effect can be estimated by comparing the overall duration of the long and the short dollar positions. Inspection reveals that during the sample period of the study interest earnings and interest costs roughly offset each other (Schulmeister, 2000).

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 models have the following trading pattern in common:

- The number of profitable trades is lower than the number of unprofitable trades.
- 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.

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.

Table 1: Pattern of DM/dollar-trading 1973/1999

	Moving average models			Momentum models		
Length i of MAS	1	3	11			
Length i of MAL	16	30	30			
Time span i				9	23	9
Lag of signal execution	0	0	0	0	0	1
Gross rate of return per year	11.12	10.10	8.33	11.53	10.66	9.20
Sum of profits per year	23.13	18.05	14.75	24.82	18.72	20.88
Profitable positions						
Number per year	9.07	4.81	3.41	12.70	7.77	7.55
Average return						
Per position	2.55	3.75	4.33	1.95	2.41	2.76
Per day	0.086	0.063	0.057	0.096	0.066	0.083
Average duration in days	29.68	59.49	75.49	20.38	36.28	33.42
Sum of losses per year	–12.01	–7.95	–6.42	–13.29	–8.06	–11.68
Unprofitable positions						
Number per year	19.62	7.22	4.11	18.96	9.59	10.92
Average return						
Per position	–0.61	–1.10	–1.56	–0.70	–0.84	–1.07
Per day	–0.125	–0.101	–0.059	–0.125	–0.097	–0.104
Average duration in days	4.88	10.90	26.25	5.60	8.65	10.31
Single rates of return						
Mean	0.388	0.840	1.108	0.364	0.614	0.498
t-statistic	4.867	4.310	3.857	5.035	4.591	4.090
Median	–0.293	–0.334	–0.265	–0.167	–0.105	–0.268
Standard deviation	2.215	3.507	4.084	2.114	2.892	2.717
Skewness	16.122	2.118	1.295	3.171	2.801	2.093
Excess kurtosis	3.274	5.326	1.790	17.253	10.072	7.527
Sample size	775	325	203	855	469	499

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 almost every model shown in table 1 exceeds 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%.

Figure 1: Distribution of trading systems by the gross rate of return
DM/dollar trading 1973 - 1999

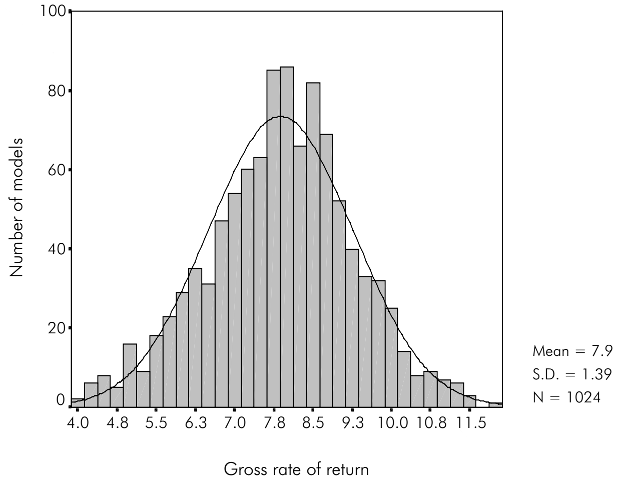
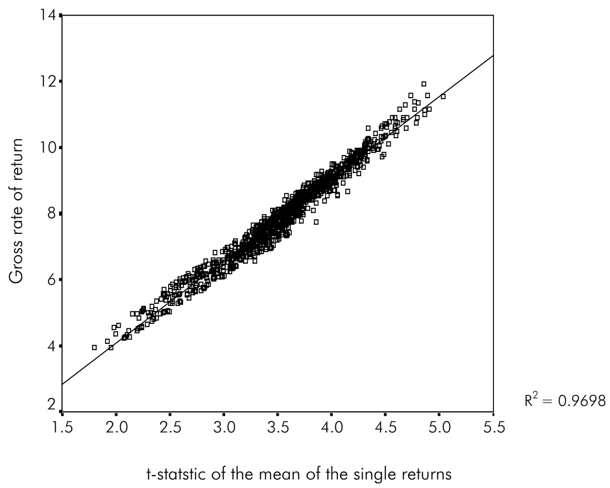


Figure 1 shows the distribution of all 1024 trading systems by their annual gross rates of return. On average they produce a mean return of 7.9% per year in the case of DM/dollar trading (9.1% in the case of yen/dollar trading). The standard deviation amounts to 1.39 (DM/dollar) and 1.13 (yen/dollar), respectively. The best performing models produce an annual return of roughly 12%, the worst models roughly 4% (DM/dollar) and 5% (yen/dollar), respectively.

Figure 2: Profitability and riskiness of 1024 technical trading systems
DM/dollar trading 1973 - 1999



The t-statistic of the mean of the single rates of return exceeds 2.5 in almost all cases (figure 2) which implies a probability of making an overall loss by blindly following these 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.

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 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. 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.

2.2.2 The pattern of profitability of technical trading models

Table 2 classifies all models according to their performance as measured by the t-statistic into four groups and quantifies 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 4.0 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 4.0 (average rate of return: 8.3%), 27.1% generate a t-statistic between 3.0 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.

Table 2: Components of the profitability of trading systems by the t-statistic of the mean of the single returns
Moving average and momentum models

DM/dollar-trading 1973-1999

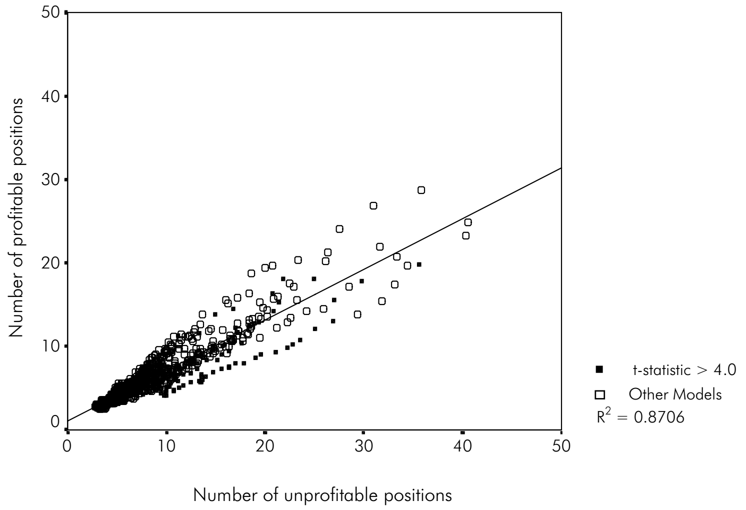
t-statistic of the Mean of the single returns	Number of models		Gross rate of return	t-statistic	Mean for each class of models					
					Profitable positions			Unprofitable positions		
	Absolute	Share in %			Number	Return per day	Duration in days	Number	Return per day	Duration in days
< 3.0	164	16.0	5.69	2.616	5.82	0.065	56.91	7.26	–0.088	20.71
3.0 - < 3.5	278	27.1	7.21	3.296	5.23	0.063	63.26	6.73	–0.083	20.58
3.5 - < 4.0	396	38.7	8.34	3.717	5.99	0.069	53.83	7.84	–0.092	15.89
> 4.0	186	18.2	9.83	4.289	7.16	0.075	43.54	11.19	–0.106	10.05
Total	1,02·	100.0	7.88	3.530	5.97	0.068	55.01	8.05	–0.091	16.87

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.

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 2).

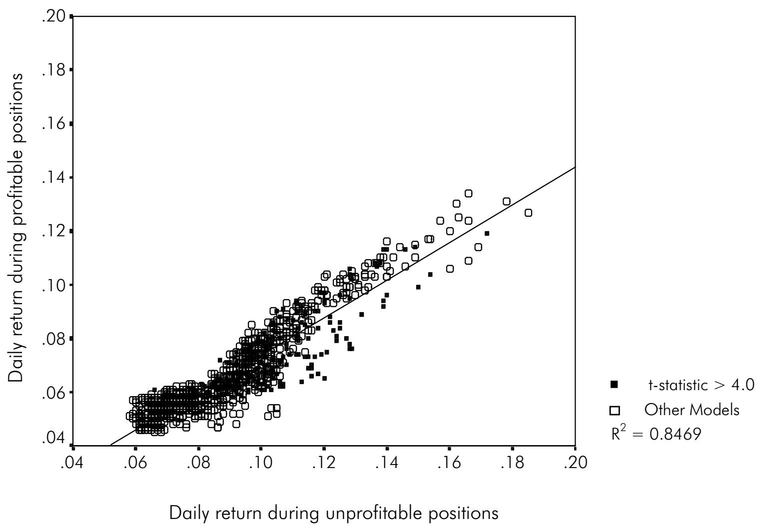
Figures 3 to 5 show the number, the daily return and the duration of profitable positions relative to the unprofitable positions for each of the 1024 models (DM/dollar trading). The models signal in almost all cases less profitable positions than unprofitable positions (the slope of the regression in figure 3 line is much smaller than 45^0).

Figure 3: Frequency of profitable and unprofitable positions
DM/dollar trading 1973 - 1999



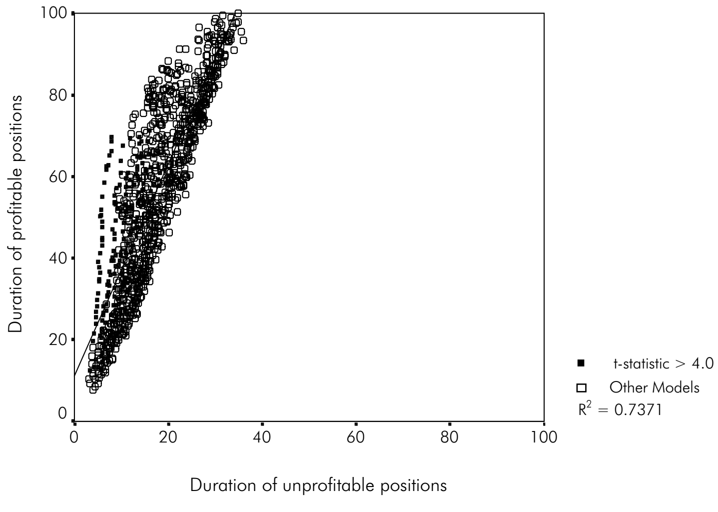
The average return per day during profitable positions is always lower than during unprofitable positions (figure 4). The trading behavior of the best performing models (t-statistic>4.0) is not significantly different from the other models as far as these two pairs of profitability components are concerned. 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 5).

Figure 4: Average daily return during 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 5: Average duration of profitable and unprofitable positions
DM/dollar trading 1973 - 1999



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). 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).

2.3 The performance of technical trading systems over subperiods

2.3.1 Performance of all models

The study divides 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.

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.

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 does not ensure the profitability of technical trading ex ante. 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. 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 "usual" exchange rate trends then it might be reproduced out of sample.

2.3.2 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 25 best models are identified on the basis of their ex-post performance (as measured by the net rate of return) over the most recent subperiod. Then the performance of the selected models is simulated over the subsequent subperiod.

Table 3 summarizes 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.

Table 3: 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 (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

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.

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 from the profitability pattern of all models and of the best models in sample. 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 only one respect. 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.

3. Aggregate trading behavior and price effects of technical models

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 positions of the 1024 technical models is calculated. 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. Finally, the relationship between the level and the change of the net position index and the subsequent exchange rate movements is analyzed.

3.1 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 (PI) 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).[2])

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).

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).

[2]) 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.

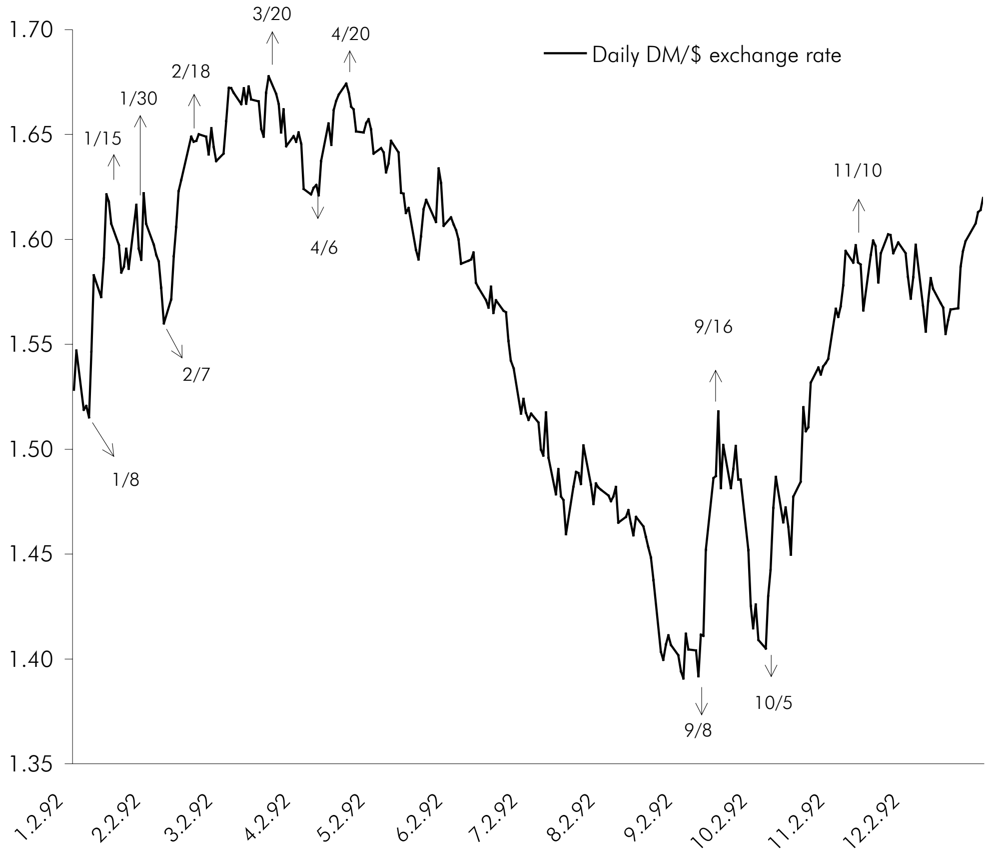
3.2 Similarities in position taking of technical models

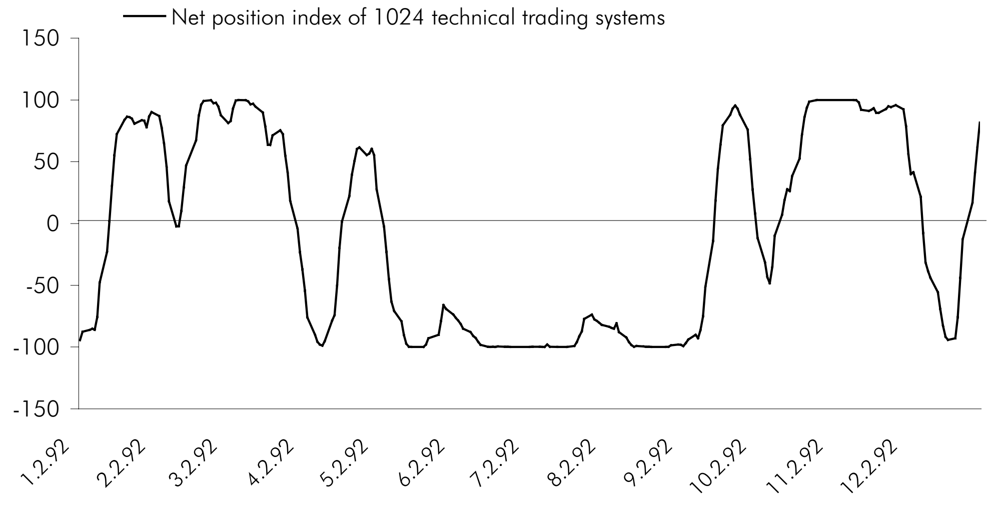
Figure 6 shows the gradual adjustment of the 1024 technical models to exchange rate movements, using DM/dollar trading over the year 1992 as example. Due to a preceding depreciation trend almost all models hold a short position on January 2. The sharp upward movement of the DM/dollar rate between January 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.

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. 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.

If one investigates the relationship between exchange rate movements and the switching of 1024 trading systems over the entire sample period the following 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. 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.

Figure 6: Aggregate trading signals and exchange rate dynamics
1992





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 if a persistent exchange rate trend occurs. 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 relationship between exchange rate movements and position switching of the 1024 technical models for the yen/dollar market is very similar to the DM/dollar market.

Table 4: 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 4 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.

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. 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.

Table 4 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 5 shows the similarity in the trading behavior of different classes of technical models. The position holding of stable models (those which are profitable over each subperiod) 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 better is the performance of the models as measured by the t-statistic 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).

Table 5: Similarity of different types of technical trading systems in holding open positions

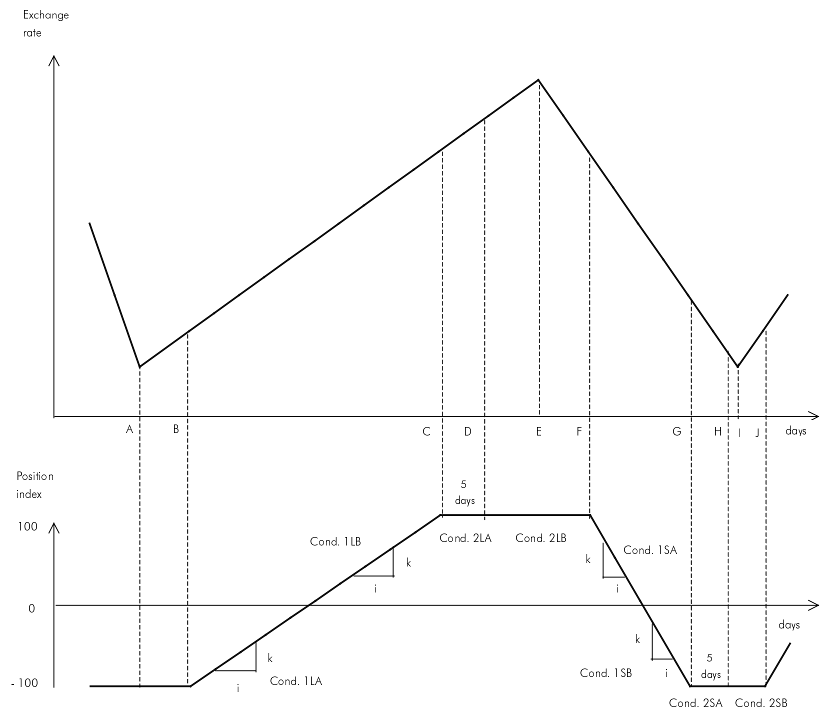
DM/dollar-trading

	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 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

3.3 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. 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 (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 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.

Figure 7: Exchange trends and aggregate positions of technical models



As a first step the possible interactions between the aggregate trading behavior of technical models and the development of 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.

The first phase of an upward trend (marked by the days A and B in figure 7) 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 C in figure 7) 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. 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.

Over the third phase of an appreciation trend all technical models hold long positions while the trend continues for some time (marked by the days C and E in figure 7). 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 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. With some lag technical models start to close the former positions and open new counterpositions (on day F in figure 7).

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: $[PI_t\text{-}PI_{t-1}]>k \cap [PI_{t-n}\text{-}PI_{t-n-1}]\geq 0 \cap [PI_t \leq 95]$
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: $[PI_t\text{-}PI_{t-1}]<\text{-}k \cap [PI_{t-n}\text{-}PI_{t-n-1}] \leq 0 \cap [PI_t \geq \text{-}95]$
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:[3])

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

Figure 7 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 models have changed their position from short (long) to

[3]) 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.

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 6 shows that the conditions 1 are rather frequently fulfilled. 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) holds 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 6: Aggregate trading signals and exchange rate movements
All models

DM/dollar-trading

Parameters of the conditions for CER		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					
k	i		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
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 i 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. However, 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 conditional exchange rate changes over the 5 (10, 20, 40) days following the realization of condition 1 have always (except for one case) the same sign as the preceding change in the position index and are in most cases significantly different from the unconditional means (table 6). Only for exchange rate changes subsequent to the realizations of condition 1L(S)[100/10] does this not hold true. 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 (table 6). 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.

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 within 5 days 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 7).

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.

Table 7 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 7). These results also hold true for the conditional ex-ante exchange rate changes in the yen/dollar market.

When looking at the four phases of technical trading related to depreciation movements the results are different in two respects (table 7). 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. 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).

Table 7: Eight phases of technical trading and exchange rate movements
All models

DM/dollar-trading

Conditions for CER_{t+j} (= Phases of technical trading)	Time span j of CER_{t+j}	(Increasing) Long positions (conditions .L.)			(Increasing) Short positions (conditions .S.)		
		Number of cases	Mean of CER_{t+j}	t-statistic	Number of cases	Mean of CER_{t+j}	t-statistic
1.A	5	174	0.2282	2.1356	520	–0.3395	–4.5745
1.B	5	519	0.1467	2.6847	182	–0.1705	–1.3130
2.A	5	869	0.3083	6.5853	977	–0.2296	–3.7636
2.B	5	296	0.1044	1.2951	330	–0.2818	–2.3237
1.A	10	174	0.1570	1.3183	520	–0.3335	–2.9125
1.B	10	519	0.1967	2.5134	182	–0.3648	–2.0661
2.A	10	869	0.4823	6.7675	977	–0.4285	–4.8477
2.B	10	296	0.2141	2.1740	330	–0.4620	–2.6656
1.A	20	174	0.2474	1.2738	520	–0.4721	–2.6038
1.B	20	519	0.3958	3.0854	182	–0.0862	0.0325
2.A	20	869	0.6726	6.8365	977	–0.7247	–5.6871
2.B	20	296	–0.1193	–0.1414	330	–0.5905	–2.4779
1.A	40	174	0.2818	1.1440	520	–0.4319	–1.2025
1.B	40	519	0.4503	2.7443	182	–0.2778	–0.3153
2.A	40	869	0.7249	5.3341	977	–1.0144	–5.2375
2.B	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 6) 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 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 feed-back 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".

4. Summary

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 risk of making an overall loss when strictly following one of these models was close to zero.
- 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.
- The out-of-sample profitability of those models which performed best in sample (i.e., over the most recent subperiod) is slightly higher than the average in-sample profitability of all models. 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.

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