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Abstract

The study analyzes the interaction between the trading behaviour of 1024 moving average and momentum models and the fluctuations of the yen/dollar exchange rate. I show first that these models would have exploited exchange rate trends quite profitably between 1976 and 2007. I then show that the aggregate transactions and positions of technical models exert an excess demand pressure on currency markets since they are mostly on the same side of the market. When technical models produce trading signals almost all of them are either buying or selling, when they maintain open positions they are either long or short. A strong interaction prevails between exchange rate movements and the transactions triggered by technical models. An initial rise of the exchange rate due to news, e. g., is systematically lengthened through a sequence of technical buy signals.

Keywords: Exchange rate; Technical Trading; Speculation; Heterogeneous Agents

JEL classification: F31; F37; G14; G15

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1. Introduction

The failure of traditional macro-based models of exchange rate determination in explaining at least some part of exchange rate fluctuations (Cheung – Chinn – Pascual, 2005) has stimulated economists to develop new approaches which focus on the micro-foundations of transaction behaviour and price dynamics. Over the past decade two approaches have become increasingly important.

The first approach focuses on modelling the interaction between heterogeneous actors in asset markets, in particular between rational traders and noise traders. This approach is computational and theoretically oriented (LeBaron, 2006, and Hommes, 2006, provide excellent surveys). By contrast, the second approach is empirically oriented. It focuses on the microstructure of foreign exchange markets, in particular on the role of order flows (Lyons, 2001; Evans-Lyons, 2002, Osler, 2006).

However, order flows are just one element in the transmission chain from (original) demand/supply to exchange rates, hence, they can hardly be interpreted as (ultimate) causes of exchange rate fluctuations. These causes have to be found in the different types of expectations formation and trading decisions driving order flows. Evans and Lyons who did most of the research in this field assume that order flows are driven by fundamentals and that they contain (private) information not (yet) incorporated in exchange rates (Lyons, 2001; Evans-Lyons, 2002; 2005A; 2005B; 2006). However, there exist also other types of trading decisions, in particular those based on technical analysis.

According to survey studies technical analysis is the most widely used trading technique in foreign exchange markets. Over the 1990s the importance of technical analysis has stronger increased than other trading practices like the orientation on fundamentals or on customer

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orders. Nowadays between 30% and 40% of professional currency traders use technical systems as their most important trading technique (Lui-Mole, 1998; Menkhoff, 1998; Cheung-Chinn-Marsh, 2004; Cheung-Wong, 2000; Cheung-Chinn, 2001; Oberlechner, 2001; Gehrig-Menkhoff; 2004, 2005, 2006; for a recent and excellent survey see Menkhoff-Taylor, 2007).

Since technical trading systems are so widely used in currency markets they are continuously monitored even by those traders who do not believe in technical analysis. By observing the transactions and open positions indicated by the most popular technical systems a trader can draw conclusions about the behaviour of other actors and their potential price effects. To put it differently: Monitoring technical models helps the trader to deal with Keynes' "beauty contest" problem, i. e., how to form expectations about other traders' expectations.

To investigate these issues, the present study focuses on the impact of the aggregate transactions and positions of 1024 trading systems on exchange rate movements in the second most active foreign exchange market, the yen/$ market. The understanding of this relationship shall be deepened by comparing the results for yen/dollar trading to those already obtained for DM/dollar trading (Schulmeister, 2006).

An analysis of the aggregate trading behaviour of technical models and their exchange rate effects might also contribute to a better understanding of the following puzzle. On the one hand, surveys indicate that fundamental news are assimilated by the market within less than 10 minutes (see, e.g., Cheung-Chinn-Marsh, 2004; Cheung-Chinn, 2001), on the other hand Evans-Lyons (2005A) report that news induce transactions and exchange rate changes lasting several days.

If one takes technical trading into consideration such protracted effects of news can be explained as follows. Any surprising announcement about fundamentals which let one expect, e. g., an appreciation of the dollar will cause news-based traders to open (additional) dollar positions. The respective order flows will drive the dollar up. In reaction to this price movement fast technical models (reacting quickly to price changes) will produce buy signals. The execution of these signals will drive the exchange rate further up. Then slower models will signal new long dollar positions, followed by models using data at lower frequencies, and so forth. Hence, it can easily take some days until slow models based on daily data produce the "last" buy signals.

The main objectives of this paper are as follows:

- Aggregate the transactions and open positions produced by 1024 technical models in the yen/dollar market between 1976 and 2007.
- Document the distribution (clustering) of aggregate transactions and positions over time. Are buy/sell transactions and long/short positions roughly in balance most of the time or are they rather concentrated on one side of the market?

- Analyze the relationship between the aggregate trading behaviour of technical models and the simultaneous as well as the subsequent exchange rate movements.
- Compare the results obtained for yen/dollar trading to the results of a study on the interaction between technical trading and the fluctuations of the DM/dollar exchange rate.

In the first part I summarize the main results of a study on the performance of 1024 technical models when trading the daily yen/dollar exchange rate (Schulmeister, 2008B). In the second (and main) part of the study, I focus on the interaction between the trading behaviour of the same 1024 models and exchange rate dynamics.

2. The performance of technical trading in the yen/dollar market

The analysis of the profitability of technical yen/dollar trading is based on 1024 moving average and momentum models. The model selection was guided by the following considerations:

- Since one cannot know precisely which models are actually used by professional and amateur traders, one should select a (relatively) great number of models of the most popular and most simple type.
- A review of the literature on technical analysis (Neely, 1997, provides an introduction; for a comprehensive treatment see Kaufmann, 1987), a survey of technical trading software as well as interviews with market participants reveal, that moving average and momentum models meet the two criteria.
- In order to avoid the suspicion of "model mining" one should select all combinations of models within a (comparatively) wide range of model parameters.
- To ensure the comparability of the results of different studies on technical trading one should stick to the same set of models, at least for the same type of market and the same data frequency.

The models used in this paper focus on the simplest form of moving average models and momentum models. The basic version of the first type of model consists of a short-term moving average (MAS) and a long-term moving average (MAL) of past prices. The trading rule 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 momentum model operates with the difference between the current price and that i days ago ($M(i) = P_t - P_{t-i}$). The trading rule is as follows: Buy (go long) when the momentum M(i) turns from negative into positive and sell (go short) in the opposite case.

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). Each model is simulated with and without a lag of signal execution by one day (such a delay filter ensures that a trade is only executed if the signal remains valid the next day). Hence, a total of 1024 different technical trading models is analyzed.

For reasons of comparability the present paper uses the same models as in two studies on the profitability of technical analysis in the DM(euro)/market and in the yen/dollar market, respectively (Schulmeister, 2008A; 2008B). The same set of models was used when analyzing the effects of technical in the DM/dollar market (Schulmeister, 2006). [1])

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

GRR = NPP*DRL*DPP – NPL*DRL*DPL

The riskiness of blindly following a technical trading model is estimated by testing the mean of the single rates of return against zero (only if it is negative does the trading rule produce an overall loss).

Table 1 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. A t-statistic greater than 4.0 is achieved by 7.7% of all models, the average rate of return per year (GRR) over these models amounts to 8.5%. The t-statistic of 32,8% of all models lies between 3.5 and 4.0 (GRR: 7,7%), 34,5 % generate a t-statistic between 3.0 and 3.5% (GRR: 6,8%). The worst performing models (t-statistic<3) still produce an average return of 5.4% per year.

[1]) The data used, the calculation of their profitability, the role of transaction costs and of the interest differential, as well as the estimation of the riskiness of technical trading are documented more in detail in Schulmeister, 2008A, 2008B).

Table 1: Components of the profitability of trading systems by types of models
Moving average and momentum models
Yen/dollar-trading 1976-2007

	Number of models									
	Abolute	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
t-statistic of the mean of the single returns										
<3.0	256	25.0	5.4	2.648	6.89	0.071	51.03	10.89	-0.094	16.42
3.0-<3.5	353	34.5	6.8	3.267	6.31	0.070	49.17	9.72	-0.092	14.95
3.5-<4.0	336	32.8	7.7	3.723	5.41	0.067	51.34	7.42	-0.083	16.80
>4.0	79	7.7	8.5	4.142	5.01	0.065	53.76	6.00	-0.075	19.17
All models	1024	100.0	6.9	3.329	6.06	0.069	50.70	8.97	-0.088	16.25

The pattern of profitability is the same for each class of models (table 1). The number of single losses exceeds the number of single profits, the average return per day (in absolute terms) is higher during unprofitable positions than during profitable positions, so that the overall profitability is exclusively due to profitable positions lasting roughly three times longer than unprofitable positions. An almost identical profitability pattern was found in the case of DM/dollar trading (Schulmeister, 2008A). One can conclude from these results that the profitability of technical currency trading stems exclusively from the exploitation of exchange rate trends.[2])

This section has shown that the profitability of technical models in currency markets is sufficiently high to cause an increasing number of market participants to use them as one basis for their trading decisions. The next section investigates the dynamics of excess demand or supply stemming from the aggregation over the different technical models.

3. Aggregate trading behaviour and price effects of technical models

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 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.

[2]) For further details on the profitability of these 1024 technical models and their components as well as on their performance over subperiods (in sample and out of sample) see Schulmeister (2008B) for yen/dollar trading and Schulmeister (2008A) for DM(euro)/dollar trading.

3.1 The aggregation of trading signals

The open positions of the 1024 models are aggregated as follows. For every trading day the number +1 (-1) is assigned to any long (short) position of each single model. The net position index (PI) is then calculated 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).[3])

The net transaction index (TI) is 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 (changed) 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 trading days (implying 2048 transactions in either case).

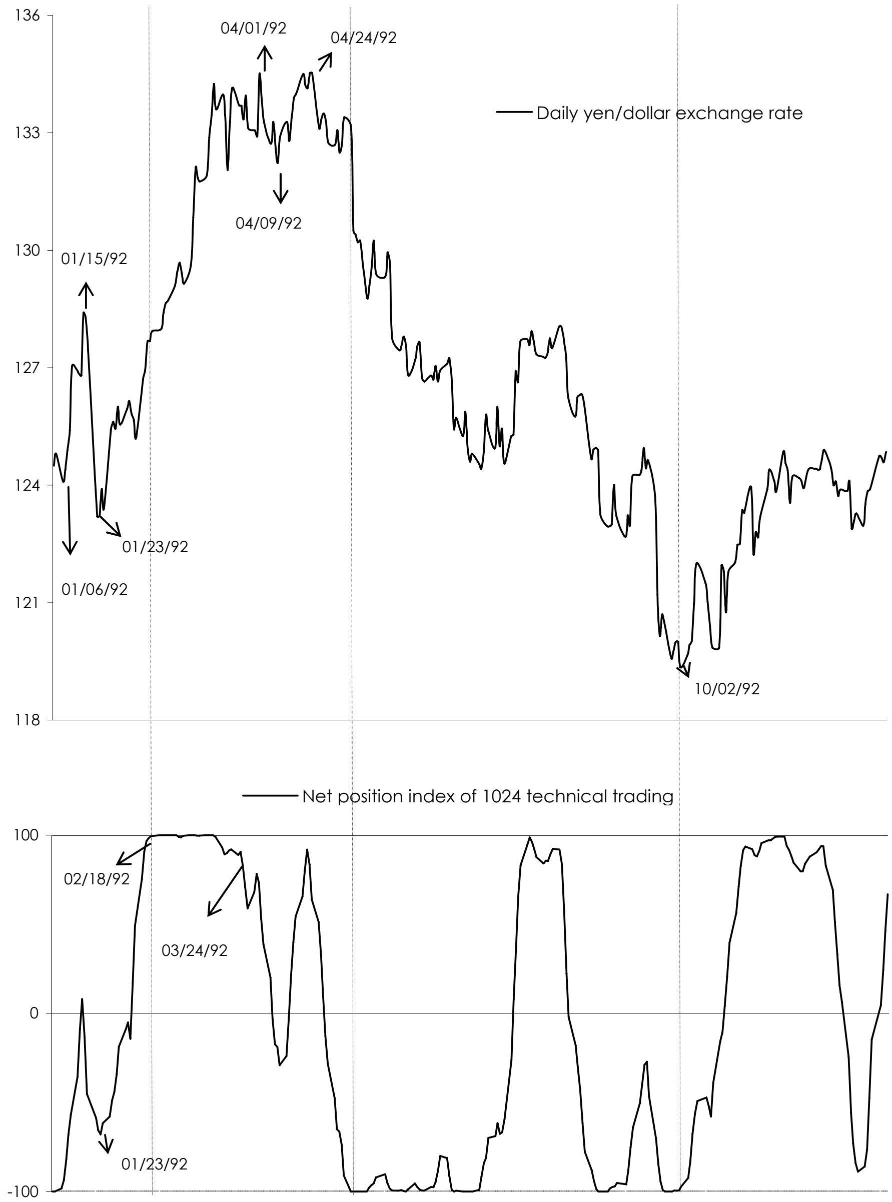
In order to investigate the extent to which the signals from technical models balance each other, the components of the net transaction index are also documented, i.e., the number of buys and sells on each trading day (divided by the number of all models).

3.2 Similarities in position taking of technical models

Figure 1 shows the gradual adjustment of the 1024 technical models to exchange rate movements, using the year 1992 as example. Due to a preceding depreciation trend all models hold a short position on January 2. The appreciation movement of the yen/dollar rate between January 6 and 15, cause roughly half of the models to switch their positions from short to long. The subsequent countermovement induces roughly 30% of the models to switch their positions. These changes are again quickly reversed due the upward trend which takes off during the last week of January. As a consequence, almost all models are holding long positions between February 18 and March 24 (most of the time the dollar continues its appreciation). During the depreciation trend of the dollar between April 24 and October 2 most models maintain a short position. In a similar way almost all models open a long position during the subsequent dollar appreciation.

[3]) 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.

Figure 1: Aggregate trading signals and exchange rate dynamics 1992



An investigation into the trading behaviour of the 1024 technical models over the entire sample reveals the following. First, most of the time the great majority of the models is on the same side of the market. Second, the process of changing open positions usually takes off 1 to 3 days after the local exchange rate minimum (maximum) has been reached. Third, it takes between 10 and 20 trading days to gradually reverse the positions of (almost) all models if a persistent exchange rate trend develops. Fourth, after all technical models have adjusted their open positions to the current trend, the trend often continues for some time.

Table 2: Distribution of time by positions and transactions of technical trading systems
Moving average and momentum models
Yen/dollar-trading 1976-1999

		Aggregate positions		
Net position index	Share in total Sample period in %	Mean of the net position index	Mean of the gross position index	
> 90	22.33	97.46	98.73	-1.27
70 - 90	10.03	81.10	90.55	-9.45
50 - 70	6.11	60.62	80.31	-19.69
30 - 50	4.93	39.95	69.98	-30.02
30 - 10	4.82	20.23	60.11	-39.89
-10 - 10	4.03	0.06	50.03	-49.97
-30 - -10	4.55	-20.31	39.84	-60.16
-50 - -30	5.26	-40.38	29.81	-70.19
-70 - -50	5.91	-60.57	19.71	-80.29
-90 - -70	10.00	-81.36	9.32	-90.68
< -90	22.02	-97.68	1.16	-98.84
Total	100.00	0.27	50.13	-49.87

		Aggregate Transactions		
	Share in total Sample period in %	Mean of the net transaction index	Mean of the gross transaction index	
> 70	0.00	0.00	0.00	0.00
50 - 70	0.02	54.98	56.64	-1.66
30 - 50	1.00	34.61	36.46	-1.85
30 - 10	14.33	16.80	19.08	-2.28
-10 - 10	69.67	0.24	3.69	-3.44
-30 - -10	13.49	-17.68	2.06	-19.74
-50 - -30	1.46	-35.50	1.71	-37.21
-70 - -50	0.04	-58.33	1.04	-59.38
< -70	0.00	0.00	0.00	0.00
Total	100.00	0.01	5.98	-5.97

Table 2 quantifies some of these observations. On 22.3% (22.0%) of all days more than 95% of the models hold a long (short) position. Hence, on 44.3% 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 69.7% of all days less than 5% of the models execute buy or sell signals (TI lies between 10 and –10). There are two reasons for that. First, the majority of the models hold the same position for most of the time. Second, the process of changing open positions evolves only gradually.

Table 2 also shows that the signals produced by technical models would cause their users to 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 almost 10 times more buy (sell) signals are produced than sell (buy) signals. 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.

Table 3: Similarity of different types of technical trading systems in holding open positions

	Yen/dollar-trading[1])			DM/dollar-trading[2])		
	Relative share of models holding the same - long or short - position					
	97.50% (|PI| > 95)	95% (|PI| > 90)	90% (|PI| > 80)	97.50% (|PI| > 95)	95% (|PI| > 90)	90% (|PI| > 80)
	Share in total sample period in %					
Types of models						
By the t-statistic of the mean rate of return						
< 3.0	27.81	36.11	47.98	37.78	44.84	57.40
3.0 - < 3.5	35.83	44.62	55.44	36.99	48.37	62.38
3.5 - < 4.0	50.03	56.79	66.49	42.17	52.20	64.96
> 4.0	52.84	72.91	81.04	46.34	56.44	66.25
By stability						
Stable models	32.39	41.62	54.41	40.79	53.49	65.41
Unstable models	38.29	47.93	59.21	36.83	47.46	60.10
All models	34.98	44.36	56.18	36.17	46.82	59.37

1) 1976/2007. - 2) 1973/1999.

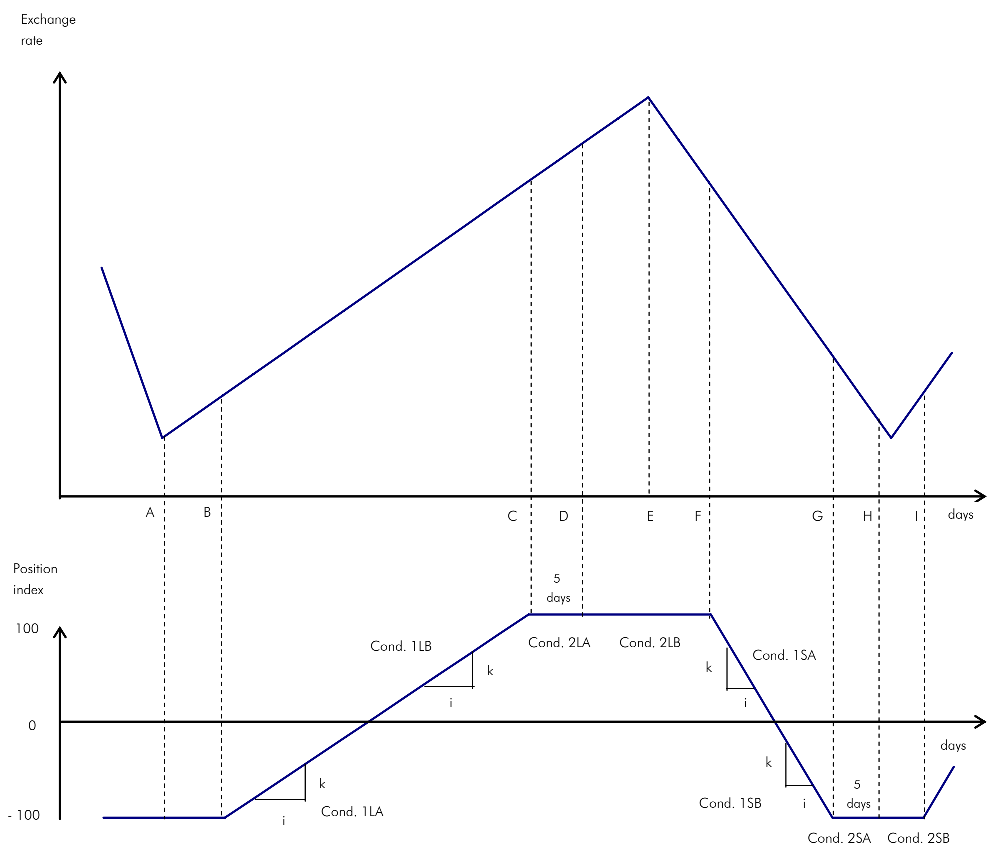
Table 3 shows the similarity in the trading behaviour of different classes of technical models. There prevails a clear relationship between the profitability and the trading behaviour of the models, e. g., the better is their performance as measured by the t-statistic the more similar is the models' position holding. E. g., more than 95% of the models hold the same open position on 72.9% of all days in the case of the best performing models as compared to 36.1% of all days in the case of the worst performing models. This difference is greater in the case of yen/dollar Trading as compared to DM/dollar trading) (table 3).

The position holding of stable models (those which are profitable over each subperiod) is less similar as compared to unstable models. The main reason for this result is the decline in the profitability of technical currency trading (based on daily data) since 2000. As a consequence, the number of stable models over the period 1976/2007 (393) is much smaller than over the period 1976/1999 (780). At the same time, the trading behaviour of the remaining stable models is more heterogeneous as compared to unstable models. This explanation is confirmed by the fact that until 1999 the position holding of stable models was more similar than the position holding of unstable models. This observation holds true for yen/dollar trading as well as for DM/dollar trading (table 3).

3.3 The interaction between technical currency trading and exchange rate movements

At first, the possible interactions between the aggregate trading behaviour of technical models and the development of an exchange rate trend shall be discussed in a stylized manner taking an appreciation trend as example.

Figure 2: Exchange rate trends and aggregate positions of technical models



The first phase of a trend (marked by A and B in figure 2) is brought about by the excess demand of non-technical traders, usually triggered off by some news (causing news-based traders to expect a dollar appreciation and, hence, to open long dollar positions).

During the second phase of an upward trend (between B and C in figure 2) technical models produce a sequence of buy signals, the fastest models at first, the slowest models al last. The execution of the respective order flows then contributes to the prolongation of the trend.

Over the third phase of the trend all technical models hold long positions while the trend continues for some time (marked by C and E in figure 2). Since technical models already hold a long position the prolongation of the trend is caused by an additional demand of non-technical traders, possibly amateur "bandwagonists" who jump later on trends than professional traders (the latter consider bandwagon effects as one of the four most important factors driving exchange rates – see Cheung-Chinn-Marsh, 2004; Cheung-Wong, 2000; Cheung-Chinn, 2001).

As the exchange rate trend continues the probability that it ends becomes progressively greater. 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 rises. 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.[4])

When the appreciation trend finally comes to an end, mostly triggered by some news, a countermovement usually takes off. With some lag technical models start to close the former positions and open new counterpositions (on day F in figure 2).

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 losses they incur during "whipsaws". Second, fast models often make losses during an "underlying" exchange rate trend as they react to short-lasting countermovements. Third, slow models open a long (short) position only at a comparatively late stage of an upward (downward) trend so that they can exploit the trend successfully only if it continues for some time.

In order to explore the interaction between exchange rate movements and the trading behaviour of technical models the following exercise is 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 behaviour of technical models. Then the difference between the means of the exchange rate changes observed under these conditions from their unconditional means 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 continuously

[4]) Note, that there are not only those contrarians who base their trading on qualifying assets as "overbought" or "oversold" but also technical traders who use "contrarian models" as described by Kaufman, 1987. An analysis of the performance of these models in the stock market is provided by Schulmeister, 2007B, 2007C.

from short to long positions over the past 3 (5, 10) business days (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). Hence, condition 1L is defined as follows.

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

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

Figure 4 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 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 3 (5, 10) 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 4 shows that the conditions 1 are rather frequently fulfilled. E. g., in 1267 (1182) 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 894 (854) 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 541 (526) 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 5 and 95, however, if k=25 then condition 1L could be fulfilled within a range of the position index between -70 and 95.

Conditions 2 occur more frequently than conditions 1. In 1391 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 slightly more frequently realized (1420 cases).

Despite the different restrictions imposed on conditions 1L(S) and 2L(S) either of them is fulfilled on 5260 days out of the entire sample of 8039 days.[5]) This behaviour of 1024 technical models can hardly be reconciled with the hypothesis that daily exchange rates follow a (near) random walk.

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. E. g., the average (relative) exchange rate change over 5 consecutive days amounts to–0.0525% between 1976 and 2007, 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 1.086%. This highly significant difference (t-statistic: 28.7) can be explained as the result of the simultaneous interaction between exchange rate movements and the changes of open positions by technical models.

The means of the conditional exchange rate changes over the 5 (10, 20, 40) days following the realization of condition 1 have the same sign as the preceding change in the position index (except for 1 out of 24 cases) and are mostly significantly different from the unconditional means (table 4).

[5]) 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

Table 4: Aggregate trading signals and subsequent exchange rate movements
Moving average and momentum models
Yen/dollar-trading 1976-2007

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 position (condition 1S)		
		Number of cases	Mean of CER_{t+j}	t-statistic	Number of cases	Mean of CER_{t+j}	t-statistic
25	-3	1267	0.6672	24.6721	1182	-0.8182	-21.6937
	5	1267	0.0256	1.7883	1182	-0.1524	-2.0812
	10	1267	0.0829	2.9573	1182	-0.3597	-3.6971
	20	1267	0.2146	4.4225	1182	-0.5641	-3.5005
	40	1267	-0.0585	2.4462	1182	-0.6510	-1.5426
50	-5	894	1.0861	28.7377	854	-1.2919	-25.6495
	5	894	0.0938	3.1617	854	-0.2208	-2.9921
	10	894	0.1596	3.9012	854	-0.4343	-4.1751
	20	894	0.1817	3.6128	854	-0.5802	-3.2284
	40	894	-0.1067	1.8430	854	-0.4948	-0.4932
100	-10	541	1.8803	33.9968	526	-2.0439	-28.7561
	5	541	0.1566	3.7359	526	-0.3067	-3.7909
	10	541	0.1986	3.6488	526	-0.5985	-5.0672
	20	541	0.1097	2.4417	526	-0.7216	-3.6456
	40	541	-0.0833	1.6398	526	-0.3666	0.1576
		More than 97.5% of all models hold the same type of open positions					
		Long positions (condition 2L)			Short positions (condition 2S)		
	5	1391	0.1281	4.0644	1420	-0.2744	-5.0217
	10	1391	0.1830	4.6716	1420	-0.4897	-6.1541
	20	1391	0.1186	3.5283	1420	-0.7870	-6.1853
	40	1391	0.0619	3.5362	1420	-1.0317	-5.0384

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): $[PI_t - PI_{t-i}] > k\ (<- k) \cap [PI_{t-n} - PI_{t-n-1}] \geq 0\ (\leq = 0) \cap [-95 \leq PI_t \leq 95]$
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.......-3, -5, -10

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.

Subsequent to the realizations of condition 2, i. e., when 97.5% of all models hold a long (short) position, the exchange rate rises (falls) much stronger than on average over the entire sample (table 4). The means of the conditional (ex-ante) exchange rate changes have the same sign as the preceding change in the position index, and are 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. The frequent continuation of exchange rate trends after conditions 2 are satisfied must be attributed to the transactions of non-technical traders ("bandwagonists") since technical traders are just keeping their positions.

Finally, the following exercise is 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 (see figure 2).

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 behaviour 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 of a trend (towards its end, trend-following models still hold long positions while the exchange rate has already begun to decline as between E and F in figure 2).

The size of the conditional ex-ante exchange rate changes differs strongly across the four phases of an appreciation trend (table 5). When 25% of the models have switched from short to long positions and more than 50% of the models are still short (condition 1LA) the appreciation movements often do not persist. Hence, the means of the conditional exchange rate changes following the realization of conditions 1LA differ only insignificantly from the unconditional means.

The ex-ante yen/dollar exchange rate changes get significantly positive 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 much smaller and even negative over two (out of four) time spans. There are two reasons for this. First, the longer a trend lasts, the higher becomes the probability of a reversal. Second, due to the long-term decline in the yen/dollar exchange rate over the entire sample period, upward trends (based on daily data) lasted shorter than downward trends.

Table 5: Eight phases of technical trading and exchange rate movements
All models
Yen/dollar-trading 1976-2007

Conditions for CER_{t+j} (= Phases of Technical trading)	Time span j of CER_{t+j}	(Increasing) Long positions (Conditions .L.)			(Increasing) Short position (Conditions .S.)		
		Number of cases	Mean of CER_{t+j}	t-statistic	Number of cases	Mean of CER_{t+j}	t-statistic
1A	5	196	0.0120	0.6676	635	-0.2532	-3.1672
1B	5	698	0.1168	3.3093	219	-0.1267	-0.6581
2A	5	1056	0.1703	4.5469	1080	-0.3032	-5.2552
2B	5	335	-0.0053	0.5166	340	-0.1828	-1.3520
1A	10	196	0.0441	1.0878	635	-0.4959	-4.2722
1B	10	698	0.1921	3.9219	219	-0.2555	-1.0464
2A	10	1056	0.2390	5.0252	1080	-0.4537	-5.0077
2B	10	335	0.0062	0.9004	340	-0.6039	-4.0040
1A	20	196	0.0718	1.3063	635	-0.6504	-3.3476
1B	20	698	0.2125	3.4611	219	-0.3764	-0.7721
2A	20	1056	0.1302	3.1298	1080	-0.6762	-4.6474
2B	20	335	0.0820	1.8872	340	-1.1391	-4.5449
1A	40	196	-0.5700	-0.5410	635	-0.5880	-0.8770
1B	40	698	0.0234	2.3372	219	-0.2243	0.4827
2A	40	1056	0.1422	3.5600	1080	-1.0766	-4.6605
2B	40	335	-0.1913	0.9695	340	-0.8890	-2.3285

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.

Exchange rate movements subsequent to the four conditions of technical trading during depreciation trends differ from the respective movements during appreciation trends in two respects (table 5):

- The means of the conditional ex-ante exchange rate changes have always the same (negative) sign as the preceding change in the position index and are more significantly different from the unconditional means as compared to appreciation trends. This difference is particularly pronounced in the case of condition 1SA as compared to condition 1LA.
- Subsequent to the realizations of condition 2SB exchange rate changes in line with the current trend are on average much larger than in the case of condition 2LB.

These two differences in the conditional ex-ante exchange rate changes between appreciation and depreciation trends are most probably due to the long-term decline in the yen/dollar exchange rate, and, hence, to downward movements of the exchange rate lasting longer than upward movements.

The results of this study are very similar to those obtained in a parallel study on the aggregate trading behaviour of technical systems in the DM/dollar market (Schulmeister, 2006). The same type of interaction between clustered sequences of either buy or sell signals and subsequent asset price movements was found when analyzing the trading signal generation of 2580 technical models in the stock index futures market based on 30-minutes-data (Schulmeister, 2007). Hence, the "stylized facts" elaborated in these three different studies might be typical for the relationship between the aggregate trading behaviour of technical models and asset price dynamics in general.

3.4 Interpretation of the results

The above analysis of the aggregate trading behaviour of technical models implies that the transactions of technical traders and of other "bandwagonists" interact with exchange rate dynamics in such a way as to bring about clusters of transactions. In turn, these clusters of either buy or sell transactions strengthen the trending behaviour of exchange rates. According to this interpretation there operates a mutually reinforcing interaction between exchange rate dynamics and technical trading strategies.

Such an interaction seems highly plausible for two reasons. First, technical analysis has become the most popular trading technique in currency markets (the respective survey studies are summarized in Menkhoff-Taylor, 2007). Second, most technical models in use are trend-following (see any textbook on technical analysis like Kaufman, 1987).

The clustering of either buys or sells as documented in this paper is in line with the phenomenon of cascades of transactions in currency markets which has been documented by Lyons (2001), Evans-Lyons (2002; 2005B), and Osler (2003; 2005). Evans and Lyons – the most prominent proponents of the microstructure approach to exchange rates - hold that order flows are only driven by new (still private) information on fundamentals (Evans-Lyons, 2002; 2005A, 2005B, 2006). However, the importance Evans and Lyons assign to order flows as the key factor in short-term exchange rate determination is not (necessarily) in contradiction to the results of the present study. This is so for the following reason: To the extent that news triggers order flows and exchange rate movements, they do also cause technical models to produce a sequence of buy or sell signals which in turn induce additional order flows.

The results of this paper might also help to better understand the following puzzle. Evans-Lyons (2005A) report that news induces transactions and exchange rate changes lasting several days. There are three reasons for why most of the delayed buy orders following a news could be induced by technical models and, hence, only indirectly by the news themselves. First, a great variety of technical models operating on different time scales is actually used in currency trading. Second, it seems implausible that professional market participants react with a delay of several days to fundamental news. Third, those surprising news don't emerge often enough to explain the size of trading volume in currency markets (even if one takes into account that customer orders often induce a series of interbank transactions - the "hot-potato-story").

The interaction between the emergence of news, technical trading and exchange rate movements also contributes to a better understanding of the phenomenon of herding in currency markets. This is so because the pattern in the signal generation of technical models causes their users to trade as if they were "herding" (Hirshleifer-Teoh, 2003, provide an excellent review of the respective literature). However, since every "technician" conceives a signal of his preferred model as private information, the concentration of transactions of technical models is caused by a common external factor, i. e., the logic of technical trading systems, and not by actual interactions between traders. Hence, the aggregate behaviour of technical models has to be considered rather as clustering and not as herding according to the taxonomy of Hirshleifer-Teoh (2003).

Finally, the results of this paper on the interaction between the aggregate trading behaviour of technical models and exchange rate dynamics provide some empirical underpinning for agent-based models. These computational and theoretically oriented models analyze the interaction between heterogeneous actors in asset markets, in particular between rational traders and noise traders.[6)] Brock-Hommes (1998) develop a theoretical model which comprises a similar case as empirically studied in this paper. "Trend chasers" make profits by getting on a trend in its early stage. These profits attract other bandwagonists who drive prices further up or down. Yet, these bandwagonists end up as loser for they got on the trend

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[6]) LeBaron, 2006, and Hommes, 2006, provide excellent surveys on these models in asset markets. The most comprehensive study of this type on the foreign exchange market is De Grauwe-Grimaldi, 2006. The price impact of moving average rules is specifically analyzed by Chiarella-He-Hommes (2005). Osler (2006) develops a microstructure-consistent exchange rate model based on the interaction between financial and commercial agents.

too late. This model has been further developed by Brock-Hommes-Wagener (2005). Their new model accounts for many different types of traders and analyzes their behaviour in an evolutionary framework.

4. Summary and concluding remarks

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

- The aggregate transactions as well as open positions of 1024 moving average and momentum models exert an excessive demand (supply) pressure on currency markets. When technical models produce trading signals they are either buying or selling, when they maintain open positions almost all of them are on the same side of the market. either long or short.
- There prevails a strong simultaneous interaction between exchange rate movements and the transactions triggered off by technical models. When these models change their open positions at a certain speed then the exchange rate changes much stronger than on average in the direction congruent with the models' transaction.
- After a certain part of technical models has reversed open positions at a certain speed, the exchange rate continues to move in the same direction as implied by the models' transactions. 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 90% of the models have already changed their open positions from short to long (long to short) the yen/dollar exchange rate continues to rise (fall) over the subsequent days.
- The continuation of exchange rate trends after most technical models have opened positions congruent with the trend has to be attributed to the transactions of non-technical traders, perhaps amateurs. At the same time, these "latecoming bandwagonists" are probably the most important losers in currency trading.

These results do certainly not prove that one can easily make money through technical currency trading. They do, however, demonstrate that the profitability of many popular models is sufficiently high to cause many practitioners to use them at least as an additional informational basis for their trading decisions. When combining the information provided by technical models with information stemming from news and order flows, market participants will try to extract the useful content of technical trading signals, i. e., the identification of trends in their early stage.

Irrespective of whether or not technical analysis provides efficient tools for profitable currency trading, the widespread use of technical models strengthens the trending behaviour of exchange rate as documented in this paper for yen/dollar trading. These feed-back effects cause foreign exchange dealers – even those who disregard technical analysis as a profitable trading strategy - to monitor the position taking of the most popular trading systems as documented by survey studies.

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

However, if one assumes that trading decisions are also influenced by emotions which are "bundled" through social interaction like "herding" into "market moods", then asset prices will often fluctuate in a sequence trends. In this world of "imperfect knowledge economics" (Frydman-Goldberg, 2007), technical analysis might be considered a reasonable strategy which aims at exploiting the trending of asset prices, and which strengthens this trending at the same time.

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