The Interaction between Technical Currency Trading and Exchange Rate Fluctuations

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Abstract

This paper examines the mutually reinforcing interactions between exchange rate dynamics and technical trading strategies. I first show that technical trading systems have been quite profitable during the floating rate period. This profitability stems from the successful exploitation of exchange-rate trends and not from taking winning positions relatively frequently. I then show that technical models exert an excess demand pressure on currency markets. When these models produce trading signals, almost all signals are on the same side of the market, either buying or selling. When technical models maintain open positions they are either long or short. Initial exchange rate movements triggered by news or by stop-loss orders are strengthened by technical trading and are often transformed into a trend. This "multiplier effect" is reflected by the close relationship between technical trading signals and order flows. Hence, order flows are not only driven by (fundamental) news but also by technical trading, which reinforces exchange rate trends to which it responds.

Keywords: Exchange rate; Technical trading; Heterogeneous agents.

JEL classification: F31; G14 ; G15

December, 2005.

WIFO

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1.　Introduction

Trading techniques based on technical analysis are widely used in financial markets. This is particularly true for the currency markets as surveys reveal. Roughly 90% of market participants base their trading at least in part on technical analysis, and between 30% and 40% of professionals use technical analysis as their most important trading technique. Moreover, the importance of technical analysis has increased more strongly over the 1990s than other trading practices like the orientation on fundamentals or on customer orders.[1]

Studies on the profitability of technical currency trading cannot fully explain the extent of the popularity of technical rules in practice. Although these studies find technical trading systems to be profitable when tested in sample, they also find the out-of-sample performance to be significantly worse. Moreover, some studies find that the profitability of trading rules based on daily data has declined over time (e. g., Marsh, 2000; LeBaron, 2002; Ohlson, 2004). The evidence on technical currency trading based on intraday data is mixed.[2]

In the first part of this study, I show which properties of technical trading systems account for their popularity among currency traders. The analysis is based on the performance of 1024 moving average and momentum models in the single most active foreign exchange market, the DM/$ market between 1973 and 1999. An out-of-sample test of the performance of all 1024 models between 2000 and 2004 (euro/US dollar) completes this part of the study. The main results are as follows:

[1] For survey studies see Group of Thirty, 1985; Taylor-Allen, 1992; Menkhoff, 1997 and 1998; Lui-Mole, 1998; Cheung-Chinn-Marsh, 2004; Cheung-Wong, 2000; Cheung-Chinn, 2001; Oberlechner, 2001; Gehrig-Menkhoff; 2004, 2005A and 2005B.

[2] For profitability studies based on daily data see Sweeny, 1986; Schulmeister, 1988; Levich-Thomas, 1993; Menkhoff-Schlumberger, 1995; Neely-Weller-Dittmar, 1997; Chang-Osler, 1999; Neely-Weller, 1999; Gencay, 1999; LeBaron, 1999; Osler, 2000; Maillet-Michel, 2000; Ohlson, 2004. Gencay-Ballocchi-Dacarogna-Olsen-Pictet (2002), Dempster-Jones (2002) and Gencay-Dacarogna-Olsen-Pictet (2003) find currency trading based on intraday data to be profitable, Curcio-Goodhart-Guillaume-Payne (1997) and Neely-Weller (2003) arrive at the opposite result.

An excellent survey of all types of studies on technical analysis in different asset markets is Park-Irwin (2004).

- Each of these models would have been profitable over the entire sample period, 91.7% would have remained profitable between 2000 and 2004.

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

- The average return per day during profitable positions is smaller than the average loss per day during unprofitable positions.

- Profitable positions last 3 to 5 times longer than unprofitable positions. Hence, the overall profitability of technical currency trading is exclusively due to the exploitation of persistent exchange rate trends.

In the second (and main) part of the study, I focus on the interaction between the trading behavior of 1024 technical models and exchange rate dynamics. In particular, I investigate the concentration of transactions on buys/sells and of open positions on long/short, and their impact on subsequent exchange rate movements. There are several motivations for such an investigation.

First, the predictive power of aggregate trading signals of different models helps individual actors to form expectations about the expectations and transactions of other actors and, hence, to tackle Keynes' "beauty contest" problem. An analysis of the impact of aggregate transactions on subsequent exchange rate movements will help to explain the omnipresence of technical analysis on the screens in trading rooms (even traders who do not follow technical signals continuously monitor the most popular models or chart techniques).

Second, such an analysis can also shed light on the causes of two characteristics in exchange rate dynamics. The first property concerns the trending behavior of the exchange rate over the long run (Engel-Hamilton, 1990), as well as over the short run (Dewachter, 2001; Neely-Dueker; 2005). The second property concerns the phenomenon of price cascades in currency markets (Osler, 2003 and 2005) and the general relationship between technical trading and exchange rate volatility (Jeanne-Rose, 2002; Bauer-Herz, 2005).

Third, an investigation into the feed-back mechanism between exchange rate movements and technical trading signals contributes to a better understanding of the transmission process from customer demand via order flow to exchange rates. Proponents of the microstructure approach hold that order flows are only driven by new (still private) information on fundamentals (Evans-Lyons, 2002; 2005A, 2005B, 2005C). However, to the extent that news impact on exchange rates, they do also cause technical models to produce a sequence of buy or sell signals which in turn induce additional order flows (the extant literature on news has neglected the multiplier effect of technical trading systems).

Finally, an analysis of the interaction between the aggregate trading behavior of technical models and exchange rate dynamics provides 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.[3])

The main results of the second part of the study are as follows:

- Most of the time the great majority of the 1024 models imply positions on the same side of the market, either long or short. In response to a new exchange rate trend, technical models change their open positions gradually within 10 to 20 trading days.

- There operates a strong feedback mechanism between exchange rate movements and the transactions triggered by technical models. When a certain portion of these models change their open positions then the exchange rate changes much stronger than on average in the direction congruent with the models' transactions.

- After a certain portion of technical models has reversed open positions the exchange rate continues to move in the same direction. This holds also true for exchange rate changes following days when 97.5% of the models hold already the same – long or short – position.

- Initial exchange rate movements triggered by news or by stop-loss orders are strengthened by technical trading and are often transformed into a trend. This "multiplier effect" is reflected by the close relationship between technical trading signals and order flows.

2.   The performance of technical currency trading

Technical analysis tries to derive profitable buy and sell signals by isolating upward and downward price trends from oscillations around a stable level, called "whipsaws" (for an introduction into technical analysis see Neely, 1997; for a comprehensive treatment see Kaufman, 1987; Murphy, 1986).

The quantitative approaches try to identify trends using statistical transformations of past prices. These models produce clearly defined buy and sell signals. The most common trading systems are moving average models and momentum models.

The first type of model consists of a short-term moving average (MAS) and a long-term moving average (MAL) of past prices. The length of MAS usually varies between 1 day (the original price series) 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

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[3]) 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. Frydman-Goldberg (2006) analyze expectations formations and transaction behavior of bulls and bears in currency markets under imperfect knowledge.

(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.

Price oscillations often cause technical models to produce "wrong" signals. In order to filter them out the following rule can be applied: Execute a signal only if it remains valid over n consecutive days.

In the following I summarize some results of a comprehensive study on the components of the profitability of technical trading systems in the DM/dollar and in the euro/dollar market between 1973 and 2004 (Schulmeister, 2005). The study comprises 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).

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. [4]

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).

Over the entire sample period all 1024 trading systems produce an annual gross rate of return of 7.9% on average, their t-statistic amounts to 3.5 on average (table 1). A t-statistic greater than 4.0 is achieved by 18.2% of all models, the average rate of return per year (GRR) over these models amounts to 9.8%. The t-statistic of 38.7% of all models lies between 3.5 and 4.0 (GRR: 8.3%), 27.1% generate a t-statistic between 3.0 and 3.5% (GRR: 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.

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[4] The selection of the models, the calculation of their profitability, the role of transaction costs and of the interest differential and the estimation of the riskiness of technical trading are documented in Schulmeister (2005). The exchange rates used are mid rates at noon in New York as published by the Federal Reserve Bank of New York (http://www.federalreserve.gov/releases/H10/hist).

Table 1: Components of the profitability of trading systems by types of models
Moving average and momentum models
DM/dollar-trading 1973-1999

t-statistic of	Number of models				Mean for each class of models					
the Mean of the single returns	Absolute	Share in %	Gross rate of return	t-statistic	Profitable positions			Unprofitable positions		
					Number per year	Return per day	Duration in days	Number per year	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
All models	1,024	100.0	7.88	3.530	5.97	0.068	55.01	8.05	−0.091	16.87
2000-2004[1]) All models out-of-sample	1024	100.0	3.82	0.775	6.00	0.069	50.66	10.12	−0.116	13.24

[1]) Euro/dollar trading.

Technical models have the following pattern of profitability in common (table 1):

- 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 4 times longer than unprofitable positions.
- The best performing models optimize the duration of profitable positions relative to the duration of unprofitable positions.

This pattern reflects the general property of technical trading models: The profits from the exploitation of relatively few persistent price trends exceed the losses from many but small price fluctuations ("cut losses short and let profits run").

The relationship between the length of the long-term moving average and the profitability of moving average models is displayed in figure 1 taking the models with MAS=1 as examples. In this case the most profitable models are those which use a long-term moving average between 15 and 35 days. The close relationship displayed in figure 1 does not imply that one can easily select profitable models ex ante (the performance of these models over subperiods as well as their out-of-sample profitability is documented in Schulmeister, 2005). However, finding such relationships as in figure 1 when searching for optimal models will attract more and more traders to use technical analysis.

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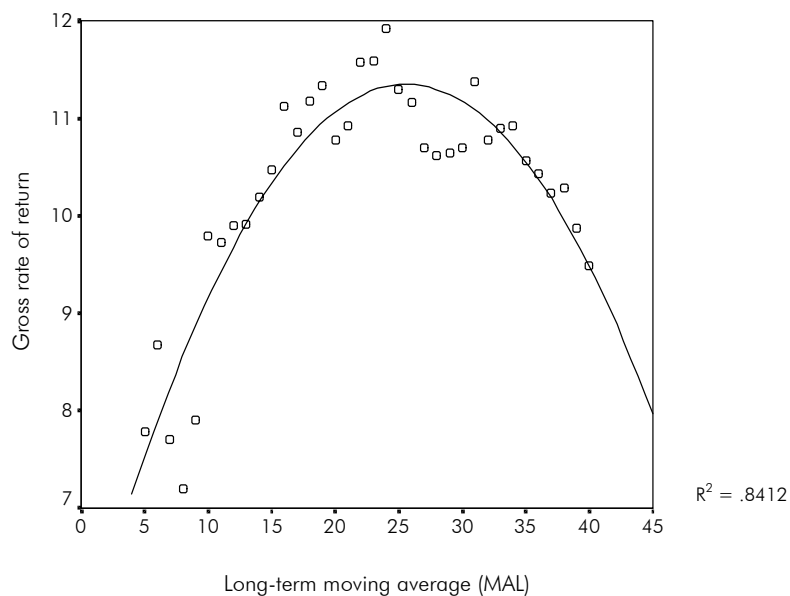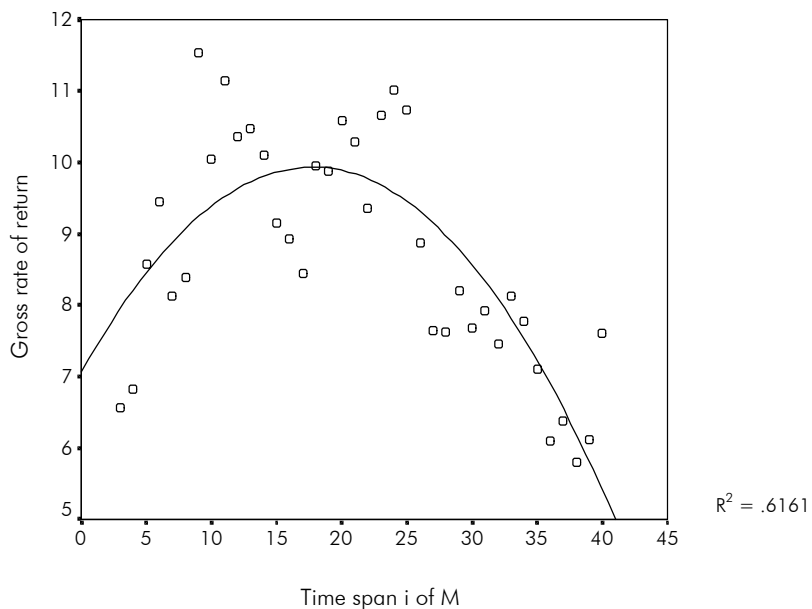*DM/dollar trading 1973 - 1999*

Figure 2: Profitability and parameter of trading systems
Momentum models with lag = 0
DM/dollar trading 1973 - 1999

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In the case of momentum models the highest profitability is achieved by those models which use a time span i between 10 and 25 days. However, the relationship between the performance of the models and the size of their parameters is less close in the case of momentum models as compared to moving average models (figures 1 and 2).

3. Aggregate trading behavior 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.

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).[5]

The net transaction index (TI) is simply the first difference of the net position index. Its theoretical maximum (minimum) value is twice as high as in the case of the net position index. 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 transactions in either case). Hence, positive (negative) values of the transactions index indicate excess demand (supply) stemming from technical trading which would also be reflected by order flows.

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 3 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 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

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[5] 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.

long. This change begins on January 9, and ends on January 21, when roughly 93% of the models are holding long positions (PI=86.5).

The sharp countermovement of the DM/dollar rate between January 30, and February 7, induces 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. 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 maintain a short position.

If one investigates the trading behavior of the 1024 trading systems over the entire sample period the following observations can be made:

- The great majority of the models is on the same side of the market most of the time, either long or short.

- The process of changing open positions in response to a new trend takes off 1 to 3 days after the local exchange rate minimum (maximum) has been reached.

- If a persistent exchange rate trend occurs it takes between 10 and 20 trading days (2 to 4 weeks) for (almost) all models to gradually turn change their open positions.

- After all technical models have adjusted their open positions to the current exchange rate trend, the trend often continues for some time.

This pattern in the signal generation of technical models implies that their users trade as if they were "herding" or "cascading" (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. In the taxonomy of Hirshleifer-Teoh (2003), the aggregate behavior of technical models has therefore to be considered as clustering and not as herding or cascading.

Table 2 quantifies some of the observations mentioned above. 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 occur on only 4.0% of all days. The fact that the great majority of technical models hold either a long or a short position for most of the time represents a strong though indirect evidence of the importance of trends in exchange rate dynamics.

Figure 3: Aggregate trading signals and exchange rate dynamics 1992
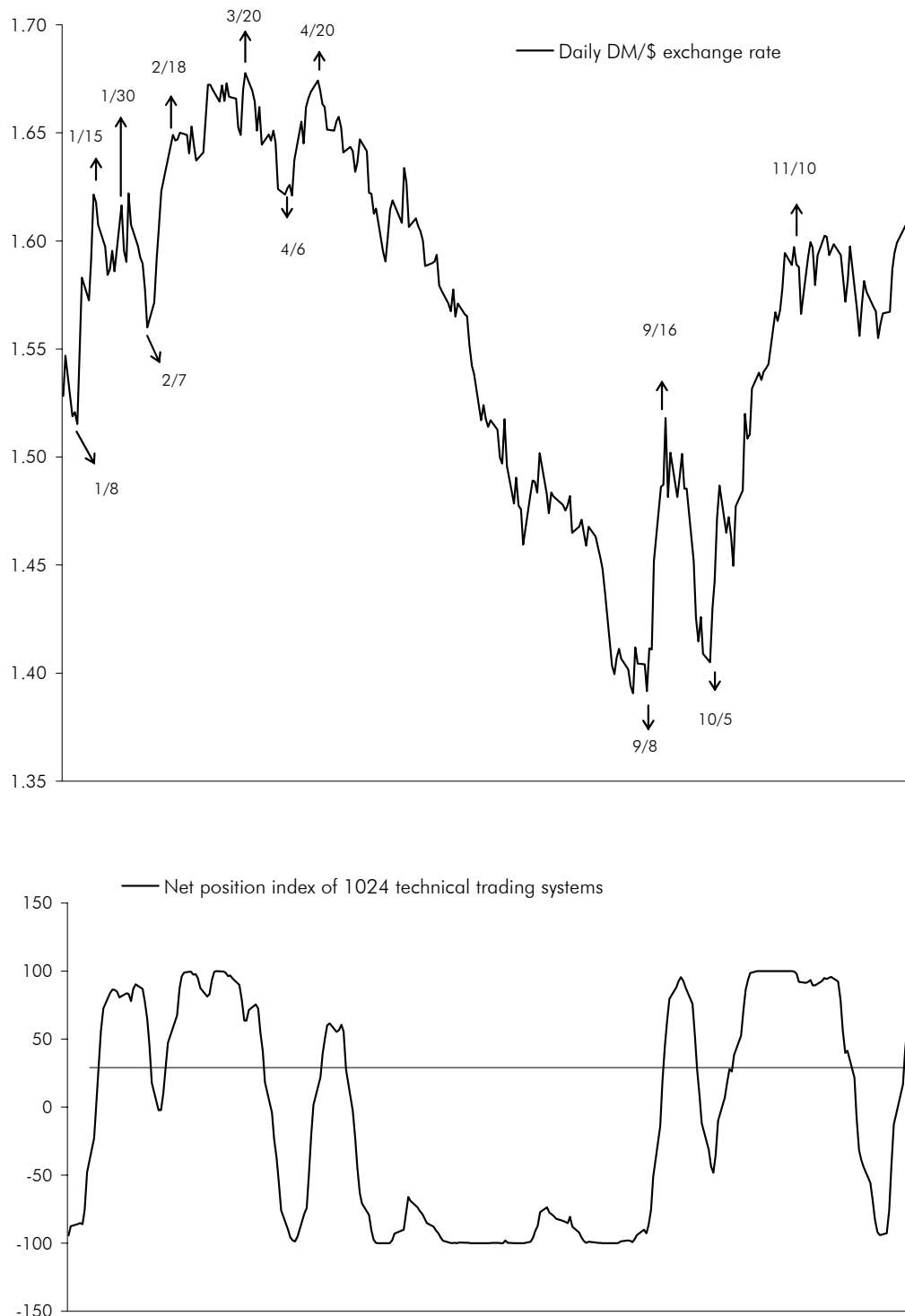
On 72.3% of all days less than 5% of the models execute buy or sell signals (the transaction index lies between 10 and –10). There are two reasons for that. First, the majority of the models hold the same – long or short – position for most of the time. Second, the process of changing open positions from short to long and vice versa evolves only gradually.

Table2: Distribution of time by positions and transactions of technical trading systems
Moving average and momentum models
DM/dollar-trading 1973-1999

		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	22.5	97.3	98.7	−1.3
70 - 90	9.8	81.2	90.6	−9.4
50 - 70	5.9	60.6	80.3	−19.7
30 - 50	4.1	40.0	70.0	−30.0
10 - 30	3.9	20.2	60.1	−39.9
−10 - 10	4.0	−0.4	49.8	−50.2
−30 - −10	3.9	−19.9	40.0	−60.0
−50 - −30	4.5	−40.6	29.7	−70.3
−70 - −50	5.9	−60.2	19.9	−80.1
−90 - −70	11.2	−81.2	9.4	−90.6
< −90	24.3	−97.5	1.3	−98.7
Total	100.0	−3.2	48.4	−51.6

		Aggregate transactions		
	Share in total Sample period in %	Mean of the net transaction index	Mean of the gross transaction index	
			Buy	Sell
> 70	0.0	0.0	0.0	0.0
50 - 70	0.1	54.4	55.7	−1.3
30 - 50	1.0	34.9	35.9	−1.1
10 - 30	12.7	17.3	19.0	−1.8
−10 - 10	72.3	0.0	3.4	−3.4
−30 - −10	12.9	−17.1	1.9	−19.1
−50 - −30	0.9	−36.1	1.2	−37.3
−70 - −50	0.1	−57.5	0.2	−57.7
< −70	0.0	−74.2	0.0	−74.2
Total	100.0	0.0	5.5	−5.5

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 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 3 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. 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 as compared to 44.8% of all days in the case of the worst performing models.

Table 3: Similarity of different types of technical trading systems in holding open positions
*DM/dollar-trading 1973-1999*

	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	30.8	40.8	53.5	65.4	82.2
Unstable models	27.8	36.8	47.5	60.1	74.9
By the t-statistic of the mean rate of return					
< 3.0	30.2	37.8	44.8	57.4	76.7
3.0 - < 3.5	26.2	27.0	48.4	62.4	81.3
3.5 - < 4.0	32.1	42.2	52.2	65.0	77.4
> 4.0	37.1	46.3	56.4	66.3	78.5
All models	27.2	36.2	46.8	59.4	74.2

1) Stable models are profitable in each of 7 subperiods, all other models are unstable.

3.3 The interaction between technical currency trading and exchange rate movements

Technical models often produce a sequence of either buy or sell signals when they are trading and hold the same – long or short – position when they are not trading. 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. At first, I shall discuss these interactions in a stylized manner. An appreciation trend is taken as example and three phases of the trend are distinguished according to the positions held by technical models (taking into account that technical trading systems are actually applied at different data frequencies would make this thought experiment more realistic – and much more complex at the same time).

Figure 4: Exchange rate trends and aggregate positions of technical models
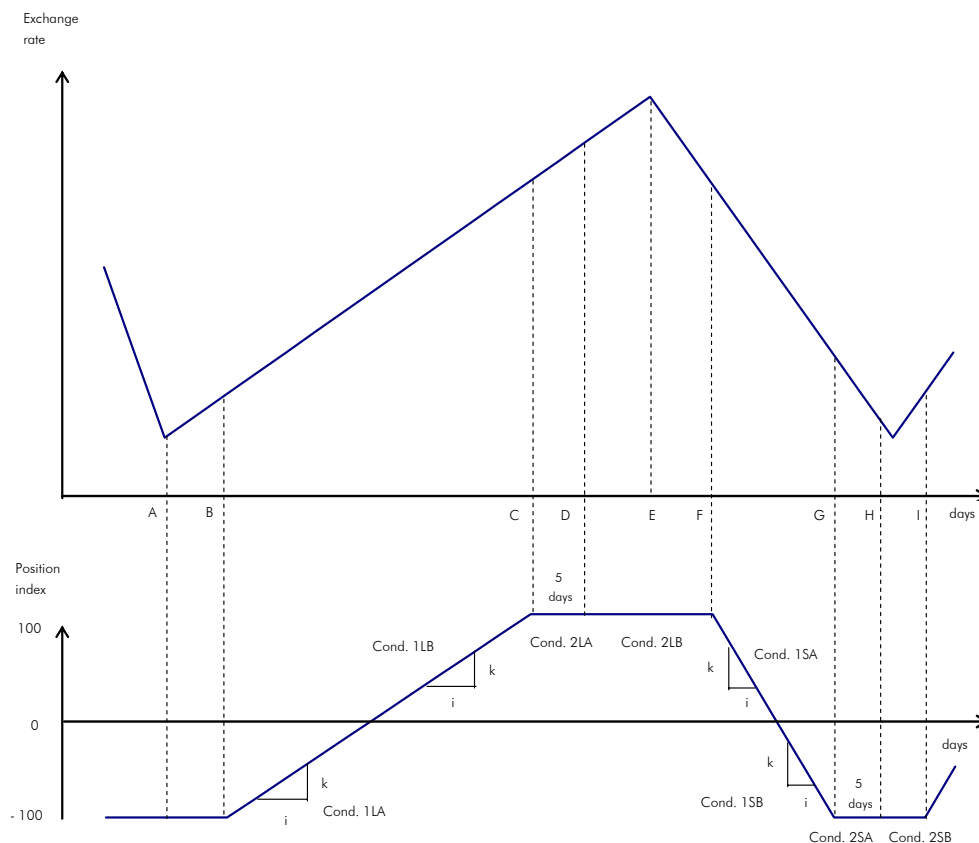
The first phase of an upward trend (marked by the days A and B in figure 4) is caused by the excess demand of non-technical traders. This additional demand will usually be triggered off by some economic or political news which let news-based traders expect an dollar appreciation and, hence, induce them to open long dollar positions. [6]

Over the second phase of an appreciation trend (between day B and day C in figure 4) technical models produce a sequence of buy signals, the fastest models at first, the slowest at last. The execution of the respective order flows then contributes to the prolongation of the trend. However, due to the transactions of other types of traders this feed-back effect might not be sufficiently strong by itself to keep the appreciation process going. If, e. g., new information causes news-based traders to reverse their positions then this might turn the exchange rate movement. In many cases, however, technical as well as non-technical

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[6] For studies on the impact of news on exchange rate see Almeida-Goodhart-Payne, 1998; Andersen-Bollerslev-Diebold-Vega, 2003; Love-Payne, 2003; Ehrmann-Fratzscher, 2004; Simpson-Ramchander-Chaudhry, 2005; Evans-Lyons, 2005C; Dominguez, 2005).

traders will 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 4). Since technical models already hold a long position the prolongation of an appreciation trend is caused by an additional demand of non-technical traders. This additional demand might stem from (amateur) "bandwagonists" who jump later on price trends than news-based traders or technical traders (practitioners 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).

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 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.[7]

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 4).

For technical currency trading to be overall profitable it is necessary that trends continue for some time after the models have taken open positions congruent with the trend. 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 closely exchange rate movements and the trading behavior of technical models are intertwined the following exercise is carried out. At first, I specify some conditions concerning different phases of technical trading and price trends. Here I focus on two types of trading dynamics. First, periods where the technical models turn around from one position to the other within a few days (condition 1). Second, periods where the models all take the same position (condition 2). Then I compare the means of the (subsequent) exchange rate changes observed under these conditions to their unconditional means.

Condition 1 is defined by the speed at which technical models switch their open position. 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) days in such a way that the position index

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[7] 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" . These models produce sell (buy) signals during the last phase of an upward (downward trend, i. e., when the trend looses momentum - see Kaufman, 1987).

(PI) increases monotonically. In addition, the condition 1L excludes all cases where more than 97.5% of the models hold long positions (these cases are comprised by condition 2L).

More formally condition 1L is defined as follows.

Condition 1L: $[PI_t-PI_{t-i}]>k \cap [PI_{t-n}-PI_{t-n-1}]\geq0 \cap [PI_t\leq 95]$

                k....25, 50, 100

                i.......3, 5, 10

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

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

Condition 1S: $[PI_t-PI_{t-i}]<-k \cap [PI_{t-n}-PI_{t-n-1}] \leq0 \cap [PI_t \geq-95]$

                k....25, 50, 100

                i.......3, 5, 10

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

Condition 2L(S) comprises all cases where more than 97.5% of all models hold long (short) positions:[8])

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 and the exchange rate j days 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 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 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 simultaneous interaction between exchange rate movements and the execution of technical trading signals.

Table 4 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

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[8]) I define one-sided position holding of technical models as all cases where the position index exceeds 95 or lies below –95. I use these values instead of (–)100 for the following reason. This study includes 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 and are therefore not used in practice (however, to avoid the suspicion of "model mining" they were not excluded from the analysis). Hence, situations where only these models change positions whereas all other models keep holding them should still be considered typical for one-sided position holding of technical trading systems.

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 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 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.[9] Such a behavior of technical models would hardly be observed if daily exchange rates followed 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 –0.027% 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 simultaneous interaction between exchange rate movements and the transactions of technical models.[10] 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 4).

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[9] 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.

[10] Klitgaard-Weir (2004) report a contemporaneous relationship between weekly changes in speculators' net positions in currency futures and exchange rate changes. Such a relationship is also implied by the findings of Danielson-Love (2004) based on high frequency data on order flows and exchange rates.

Table 4: 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					
			From short to long positions (condition 1L)			From long to short positions (condition 1S)		
k	i		Number of cases	Mean of CER_{t+j}	t-statistic	Number of cases	Mean of CER_{t+j}	t-statistic
25	3	-3	951	0.835	22.520	953	−0.793	−21.537
		5	951	0.145	3.528	953	−0.221	−3.837
		10	951	0.215	3.665	953	−0.344	−4.047
		20	951	0.287	3.238	953	−0.353	−2.260
		40	951	0.198	2.131	953	−0.356	−1.171
50	5	-5	693	1.397	27.501	702	−1.271	−25.547
		5	693	0.167	3.342	702	−0.296	−4.543
		10	693	0.187	2.787	702	−0.342	−3.479
		20	693	0.359	3.264	702	−0.372	−2.137
		40	693	0.408	2.901	702	−0.392	−1.179
100	10	-10	406	2.503	29.537	404	−2.197	−27.509
		5	406	0.012	0.521	404	−0.273	−3.180
		10	406	−0.156	−0.909	404	−0.189	−1.246
		20	406	0.023	0.648	404	−0.261	−1.012
		40	406	0.181	1.283	404	−0.168	−0.038

	More than 97,5% of all models hold the same type of open position					
	Long positions (condition 2L)			Short positions (condition 2S)		
5	1165	0.257	5.992	1307	−0.243	−4.307
10	1165	0.414	6.789	1307	−0.437	−5.369
20	1165	0.471	5.770	1307	−0.691	−5.965
40	1165	0.527	4.834	1307	−0.975	−5.815

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.

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 4). 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.

The last phase of an exchange rate trends must be attributed to the transactions of non-technical traders.[11]) These "bandwagonists" (perhaps amateurs) continue to exert an excess demand on the market. Their behavior lengthen exchange rate trends and, hence, cause technical models to be overall profitable. These "latecomers" are probably the most important losers in currency trading, even though they can hardly be identified, in part because the "membership" to this group strongly fluctuates (due to the trading losses).[12])

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 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 4).

- 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 of a trend. Note, that towards the end of this

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[11]) It seems highly unprobable that slower models than the slowest models included in this study are actually used in practice.

[12]) Brock-Hommes (1998) provide a theoretical model which comprises a similar case. "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 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 behavior in an evolutionary framework. Note, that there are also other types of losers in currency trading besides the "latecoming bandwagonists". Central banks, e. g., will systematically lose insofar as their interventions unsuccessfully "lean against the wind".

phase trend-following models still hold long positions while the exchange rate has already begun to decline (between E and F in figure 4).

Table 5: 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	0.228	2.136	520	−0.340	−4.575
1.B	5	519	0.147	2.685	182	−0.171	−1.313
2.A	5	869	0.308	6.585	977	−0.230	−3.764
2.B	5	296	0.104	1.2955	330	−0.282	−2.324
1.A	10	174	0.157	1.318	520	−0.334	−2.913
1.B	10	519	0.197	2.513	182	−0.365	−2.066
2.A	10	869	0.482	6.768	977	−0.429	−4.848
2.B	10	296	0.214	2.174	330	−0.462	−2.666
1.A	20	174	0.247	1.274	520	−0.472	−2.604
1.B	20	519	0.396	3.085	182	−0.086	0.033
2.A	20	869	0.673	6.837	977	−0.725	−5.687
2.B	20	296	−0.119	−0.141	330	−0.591	−2.478
1.A	40	174	0.282	1.144	520	−0.432	−1.203
1.B	40	519	0.450	2.744	182	−0.278	−0.315
2.A	40	869	0.725	5.334	977	−1.014	−5.238
2.B	40	296	−0.053	0.448	330	−0.859	−2.954

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 4) 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 ≤ PI_t ≤ 95} and.....

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

Condition 1L (S) B: More than 50% of the models hold long (short) positions, i.e. $PI_t ≥ 0$ ($PI_t ≤ 0$).

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.

Table 5 shows that the size of the conditional ex-ante exchange rate changes differ strongly and systematically across the four conditions 1LA, 1LB, 2LA and 2LB (during 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 (during 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 even negative when measured over the time span j = 20 and 40 days (in the last phase of an upward trend the probability of negative exchange rate changes between day (t) and day (t+n) increases with n – see also figure 4).

Exchange rate movements following the four phases of technical trading during depreciation trends differ from the movements subsequent to the respective phases during appreciation trends in two respects (table 5). 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 exchange rate changes are in line with the current trend (i. e., negative) and are on average 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 two facts. First, over the entire sample period short downward movements of the DM/dollar exchange rate were often steeper than short upward movements and, second, downward trends lasted longer than upward trends. Both observations are most probably related to the dollar depreciating over the long run between 1973 and 1999.

The strong interaction between technical trading and exchange rate dynamics contributes to a better understanding of price and transactions cascades in currency markets. These cascades are mostly attributed to stop-loss orders (Osler, 2003 and 2005) or to news about fundamentals (Evans-Lyons, 2005A). The results of this study suggest that initial exchange rate movements triggered by stop-loss orders or by news will be lengthened and strengthened by technical trading. This multiplier effect of technical trading might also account in part for the close relationship between customer order flow and subsequent exchange rate movements found to prevail in general (Lyons, 2001; Evans-Lyons, 2002, 2005B).

It seems highly probable that this multiplier effect has strongly contributed to the size of trading volume in currency markets since surprising news do not emerge often enough to explain this phenomenon (even if one takes into account that customer orders often induce a series of interbank transactions as described in the "hot-potato-story" by Lyons, 2001).

To explore the issue of what drives order flows I compare the (net) transactions stemming from the 1024 models with the data on order flows in DM/$ trading used by Evans-Lyons (2002) as shown in figure 5. A simple regression of order flows on the contemporaneous transactions index (both in first differences) reveals that changes in transactions induced by technical models account for 30% of the variance of order flow changes (the t-statistic of the coefficient of the transaction index is 5.77).

Figure 5: Technical trading signals and order flows

May to August 1996
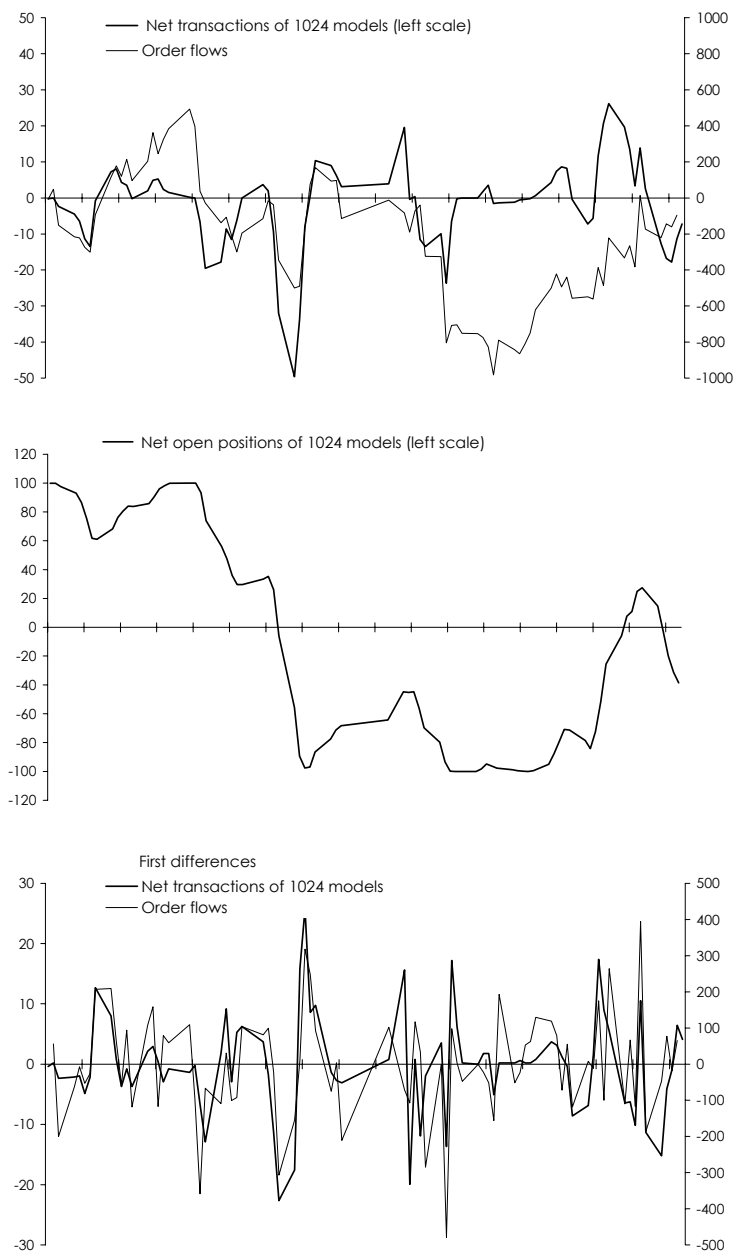
However, on days when technical models are just holding an open position they will not influence order flows. Also, the 1024 models comprise some extremely price sensitive models which produce signals when almost all other models keep holding their position (these signals will not influence order flows if these models are not used in practice – see also footnote 8). In order to account for these two factors I leave out all days on which the position index exceeds |95| and |90|, respectively. This holds true for 23 and 28 days, respectively, out of

the overall sample of 76 days (figure 5). According to regressions based on these restricted samples, transactions of technical models account for 39% (45%) of the variance of order flow changes (the t-statistic of the coefficient of the transaction index rises slightly to 5.89 and 6.31, respectively).

These preliminary results together with the surveys of practitioners on the use of technical analysis suggest the following. Order flows in currency markets are not only driven by new (still private) information on fundamentals but also by technical trading and by the demand of other (latecoming) "bandwagonists".[13]

4.   Summary and concluding remarks

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

- Each of the 1024 technical models investigated would have been profitable in the DM/dollar market between 1973 and 1999 based on daily data. In the out-of-sample period between 2000 and 2004, 91.7% of the models would have remained profitable.

- The profitability of technical currency trading is exclusively due to the exploitation of persistent exchange rate trends since profitable positions last on average several times longer than unprofitable positions.

- The aggregate trading behavior of technical models exerts an excess demand pressure on currency markets. First, when technical models produce trading signals, almost all signals are on the same side of the market. Second, when technical models maintain open positions they are either long or short.

- A strong feed-back mechanism operates between exchange rate movements and the transactions of 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 portion of technical models has reversed open positions the exchange rate continues to move in the same direction. This holds also true for exchange rate changes following days when 97.5% of the models hold already the same – long or short – position.

- Order flows are not only driven by fundamentals but also by technical trading signals, and most probably also by the demand of "latecoming bandwagonists".

These results indicate that there is a wide gap between the actual expectations formation and transaction behavior of technical traders and the (oversimplifying) assumptions made in theoretical models which take feed-back traders into account. These models mostly assume

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[13] Danielson-Love (2004) provide strong (indirect) evidence on the importance of feedback trading for the dynamics of order flows and exchange rates (they analyze the interaction between these variables based on high frequency data, i. e., for 1-minute and 5-minute intervals).

that feed-back traders just follow the most recent price movement, e. g., they buy whenever the price is rising. Such an assumption does not hold true for technical trading. This is so because any technical model produces only one signal per (expected) trend.[14]

Also, technical trading does not imply a simple forecast through extrapolation as is assumed in theoretical models of noise trading. The expectation implied by following a technical trading system concerns the pattern of asset price dynamics as a whole. It is assumed that persistent price movements occur sufficiently often so as to more than compensate a technical trader for the more frequent losses caused by minor fluctuations. This type of expectations formation reduces the complexity of making trading decisions to the minimum required for earning profits in "trending" asset markets.

Finally, it should be noted that any assessment of technical trading depends on how one "frames" his perception of the expectations formation, transactions behavior and price dynamics in asset markets. If one assumes that there exists perfect knowledge and that almost all market participants act as utility maximizing individuals forming expectations according to the unique true model, then technical trading would not exist or would be quickly wiped out by rational speculators (this is the rational expectations view). Alternatively, if one assumes that markets are often less efficient, that there exist limits to arbitrage, particularly due to risk, then technical traders (as some kind of noise traders) can cause persistent mispricing of an asset. At the same time their trading is considered irrational and not profitable (this is the behavioral finance view).

If one assumes that human knowledge is essentially imperfect, that a unique true (fundamental) model does not exist due to heterogeneous perceptions of the world (like economic theories) and that the decisions of all actors are governed not only by reason but also by emotions which are "bundled" through social interaction into "market moods", then one might expect asset prices to fluctuate in a sequence of "bull markets" and "bear markets" around some kind of fundamental "attractor" (this view underlies the "imperfect knowledge economics" approach as developed in Frydman-Goldberg, 2006). In such a "world" technical trading can be considered as the result of learning and exploiting regularities in asset price dynamics. It represents a disciplined trading technique which aims at avoiding exactly that emotions-driven misbehavior which is investigated by behavioral finance. At the same time it is this misbehavior of other actors like the "latecoming bandwagonists" which causes technical models to be profitable.

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[14] For theoretical treatments of noise traders see De Long-Shleifer-Summers-Waldmann, 1990A and 1990B; Frankel-Froot, 1990; Cutler-Poterba-Summers, 1991; Hong-Stein, 1999; Daniel-Titman, 2000.

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