NOISE TRADING AND THE EFFICIENCY OF FINANCIAL MARKETS

An Investigation into the Dynamics of Exchange Rates and Stock Prices

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This paper draws heavily on two previous studies on the profitability of technical trading systems in the foreign exchange market (Schulmeister1987) and in the stock market (Goldberg and Schulmeister 1988). We greatefully acknowledge financial support from the C. V. Starr Center for Applied Economics and from the Wissenschaftszentrum Berlin für Sozialforschung. The empirical work was done at the Austrian Institute of Economic Research and we are therefore particularly grateful to Eva Horvath who did all of the statistical work and to Marianne Riese who wrote the computer program for the analysis of the profitability of technical trading rules. We are also grateful to Roman Frydman and Damien King for their many helpful comments. A special thanks goes to Erna Kernreich for typing the manuscript.

1. Introduction

In the *General Theory*, Keynes distinguished between types of activities in the stock market — speculation and enterprise:

> If I may be allowed to appropriate the term *speculation* for the activity of forecasting the psychology of the market, and the term *enterprise* for the activity of forecasting the prospective yield of assets over their whole life, it is by no means always the case that speculation predominantes over enterprise. As the organisation of investment markets improves, the risk of the predominance of speculation does, however, increase. In one of the greatest investment markets in the world, namely, New York, the influence of speculation (in the above sense) is enormous (KEYNES 1964, p. 158p.).

In the parlance of today's economics, Keynes' speculators would be called noise traders. Such traders are interested only in the «psychology of the market», i.e., in «discovering what average opinion believes average opinion to be» (Keynes 1964, p. 159). Many of these market players attempt to profit from continuously buying and selling financial assets in the short run, without any concern for their long run prospective yields. In other words they completely ignore market fundamentals. Instead, they subscribe to a wide assortment of technical trading techniques, which in many cases merely extrapolate the most recent short-run price movements (i.e., only the information contained in past prices is used). The use of such technical trading strategies has increased strongly in the financial markets of the 1970s and 1980s[1]. This growth, however, runs counter to one of the most firmly rooted beliefs in economics and finance, namely, that financial markets are efficient. According to this view, no unexploited profit opportunities should be available in the market, i.e., market agents should be unable to earn returns systematically in excess of equilibrium expected returns (see Fama 1976). As such, noise trading is irrational and should be absent from the market. Efficient market theorists explain this apparent anomaly by recognizing that price runs, althoug unsystematic, do exist in an efficient market. A particular technical rule, therefore, may seem to be profitable during any given time period, thus causing market agents to believe mistakenly that they have found a way to beat the market. But, given a sufficient amount of time, such traders will find that their rules are relatively unprofitable on average (see Elton and Gruper 1984 and Tomek and Querin 1984). Efficient market theorists thus view the presence of technical noise trading as a rather transient phenomenon.

The purpose of the present paper is twofold. First, it reports the findings of a number of trading rule tests that were conducted in both the foreign exchange market and the stock market, using the dollar-deutschemark exchange rate and the S&P 500 and Dow Jones 30 price indices for the most recent experience of the 1970s and 1980s. The aim here is to test whether the foregoing view on noise trading is accurate, i.e., whether technical noise trading is an unprofitable and therefore transient phenomenon. The tests differ from earlier attempts in that: 1) we examine the profitability of several of the most popular technical trading techniques in both markets; and 2) we use hourly data and take into account the low cost of futures contracts in testing the trading rules in the market for stock[2]. The paper's second purpose is to contrast the findings of the trading rule tests in the foreign exchange market with those in the stock market. In doing so, we attempt to uncover certain features which may be characteristic of speculative prices in general. To this end, we also rely on some rather unconventional methods in quantifying the price dynamics in the two markets.

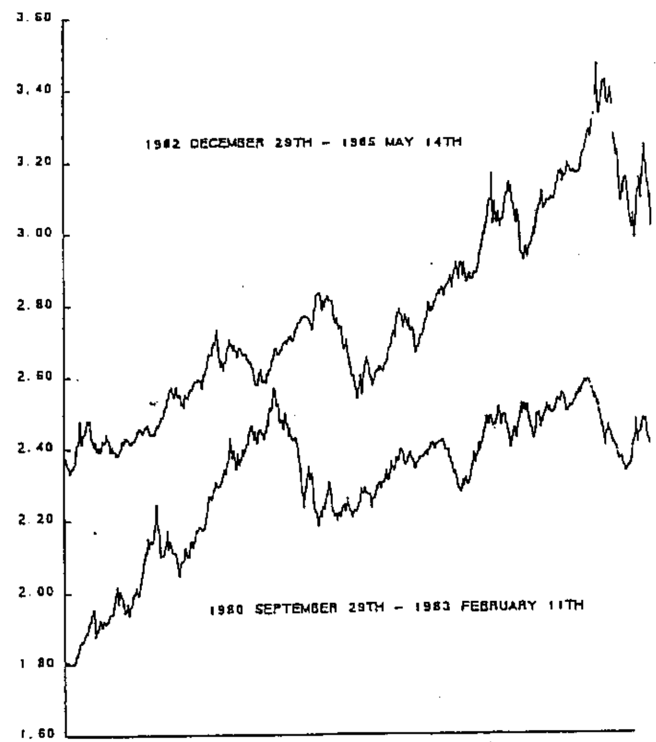
The structure of the paper is as fallows. Section 2 elaborates upon the pattern of exchange rate and stock price movements. It is shown that a sequence of persistent upward and downward price runs, which are interrupted often by erratic fluctuations, is most typical of the dynamics of speculative prices in the short run. Section 3 presents the results of the trading rule tests based on gross returns. The analysis finds that the most popular technical trading systems have outperformed consistently the buy and hold strategy in both the foreign exchange market and the stock market by considerable margins. Hence, price movements in both markets are found to involve systematic price runs and to contain information relevant for predicting future price movements. In Section 4, we adjust gross returns for the cost of transacting. We find that the trading rules are quite profitable in the foreign exchange market, again consistently outperforming the buy and hold. In the stock market, the analysis reveals that while these rules are most likely unprofitable in the cash market for stock, they are extremely profitable in the futures markets for stock, the difference in profitability owing to the fact that futures transactions entail substantially lower transaction costs as well as lower margin requirements than do cash transactions. Thus, the information contained in past price movements is found to be exploitable in both the foreign exchange market and the market for stock, if the latter market is broadly defined to include stock index futures (and options), i.e., both the foreign exchange market and the stock market are found to be inefficient. Section 4 concludes with a short discussion on the importance of futures markets for technical noise trading. In Section 5, we report the results of an out-of-sample case study on the profitability of technical analysis during the month of October 1987. The object here is to examine the extent to which technical noise trading might have contributed to the stock market crash of October 19, 1987. The results provide indirect evidence that such trading did play a significant role in the collapse. Section 6 concludes the paper with a discussion on some of the puzzles the analysis raises.

2. Some Observations on the Pattern of Speculative Prices

In order for technical analysis to be profitable, the dynamics of speculative prices must involve exploitable regularities. In this section we make use of some rather nonstandard methods in order to examine this issue. These methods are able to quantify several specific characteristics inherent in the daily movements of speculative prices. The findings here will provide us with a foundation upon which to analyze the trading rule results.

Figure 1 shows that the dollar appreciated between 1980 and 1985 in a sequence of upward and downward runs (monotonic or «almost» monotonic movements), which were interrupted ra-

DAILY MOVEMENTS OF THE DM/$ EXCHANGE RATE (1980-1985) Figure 1



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ther frequently by oscillations around a constant level (this phenomenon is referred to as «whipsaws» by professional traders). It is clear that such a stepwise appreciation can be brought about in two different ways (or in some comination of the two). In one case, the appreciation runs may be steeper on average than the depreciation runs and it the other case the appreciation runs may last longer on average than the depreciation runs. Table 1 sheds light on this issue by separating the single appreciation runs from the single depreciation runs for the period between October 1980 and September 1986[3]. The table indicates that the overall dollar appreciation which occurred between 1980 and

early 1985 was mainly due to the difference in the length of the appreciation and depreciation runs rather than to the difference in their slope. The upward runs lasted on average 7.19 days, while the downward runs lasted on average only 4.62 day. At the same time, the upward runs were only slightly steeper than the downward runs (0.53 Pfennig per day compared to -0.48 Pfennig per day). Similarly, the overall dollar depreciation which began in early 1985 was mainly due to the fact that the downward runs lasted almost twice as long as the countermovements (6.97 days as compared to 3.71 days).

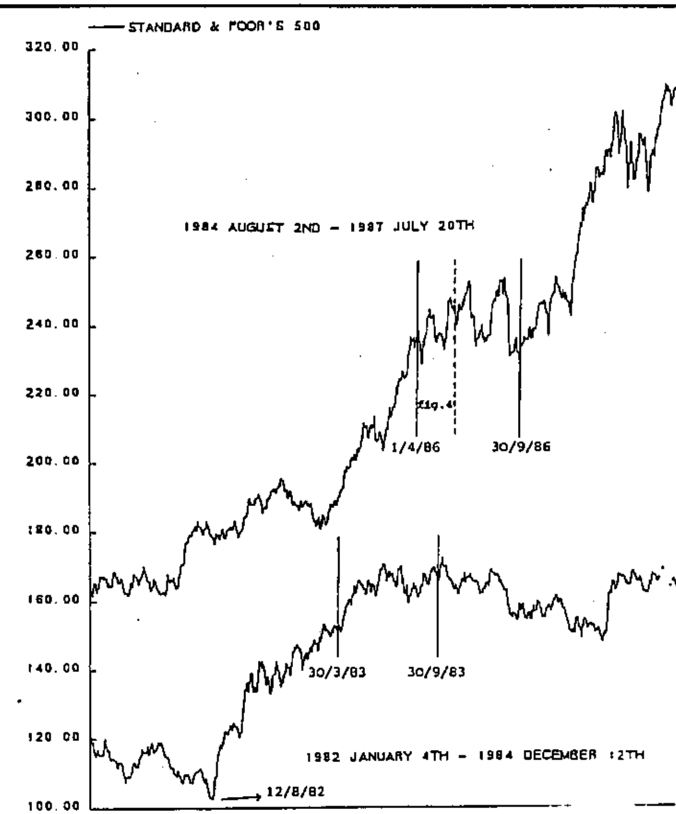
The importance of persistence in exchange rate runs for the overall process of appreciation and depreciation in the medium-term (i.e., for medium-term trends) can be seen quite clearly by classifying the single upward and downward runs according to their duration. Table 1 shows that almost half of the 256 (twice 128) runs which occurred over the period between October 1980 and September 1986 lasted only 3 days or less; at the same time their slope (the change in level per day) was far below average. Thus, these shorter movements contributed very little to the overall process of appreciation and depreciation. If one sums the changes in level over all upward runs, one obtains a hypothetical appreciation of 415.3 Pfennig ($128 \times 6.24 \times 0.52$). It turns out that the 54 shortest movements contributed only 23.8 Pfennig (5.7 percent) to this overall appreciation, whereas the contribution of the 11 longest runs was much greater (154.0 Pfenning or 37.1 percent). This phenomenon is even more extreme for the downward runs. The 10 longest downward runs accounted for 50.6 percent of the overall hypothetical depreciation. Another way to view this is to focus on runs lasting 10 business days or more. It can be seen that the 27 longest upward runs accounted for 81.2 percent of the overall hypothetical appreciation and the 17 longest downward runs contributed 73.3 percent to the overall hypothetical depreciation. The reason for this concentration lies in one fact which is extremely important for an understanding of the profitability of technical analysis. Exchange rate runs tend to be steeper the longer they last (compare columns 2/3 and 5/6 in Table 1). Consequently, the profit from the correct identification of one lon-

Table 1: Classification of Monotonic Paths (Runs) of the Daily DM/$ Exchange Rate by Duration[1]

Date	Duration in days	Appreciation Paths: Number	Appreciation Paths: Average duration in days	Appreciation Paths: Average change in level in Pfennig per day	Depreciation Paths: Number	Depreciation Paths: Average duration in days	Depreciation Paths: Average change in level in Pfennig per day
		(1)	(2)	(3)	(4)	(5)	(6)
80/10/08-85/03/06	- 3	33	1.45	0.27	51	1.57	—0.33
	3- 5	13	4.62	0.47	14	4.86	—0.45
	5- 7	11	6.27	0.73	13	6.31	—0.71
	7-10	12	8.92	0.68	6	8.33	—0.89
	10-15	13	13.40	0.76	2	12.00	—1.07
	15-	11	19.18	0.73	6	20.00	—0.79
	Total	93	7.19	0.53	92	4.62	—0.48
85/03/06-86/09/19	- 3	21	1.62	0.32	9	1.00	—0.31
	3- 5	8	4.75	0.49	8	4.88	—0.36
	5- 7	2	7.00	0.61	6	6.50	—0.76
	7-10	1	10.00	1.22	4	8.75	—1.19
	10-15	3	11.33	1.43	5	12.60	—0.93
	15-	—	—	—	4	16.50	—1.34
	Total	35	3.71	0.49	36	6.97	—0.74
80/10/08-86/09/19	- 3	54	1.52	0.29	60	1.48	—0.33
	3- 5	21	4.67	0.48	22	4.86	—0.49
	5- 7	13	6.38	0.71	19	6.37	—0.72
	7-10	13	9.00	0.72	10	8.50	—1.01
	10-15	16	13.00	0.88	7	12.40	—0.97
	15-	11	19.18	0.73	10	18.60	—1.01
	Total	128	6.24	0.52	128	5.27	—0.55

[1] 5 days moving average.

DAILY STOCK PRICE MOVEMENTS ON THE NEW YORK STOCK EXCHANGE (1982-1987) — Figure 2



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ger lasting run can easily compensate for the many smaller losses that occur during sequences involving shorter lasting movements (whipsaws).

Figure 2 suggests that the pattern of short-term stock price movements is quite similar to that of exchange rates, i.e., it also consists of a sequence of persistent upward and downward runs and whipsaws. The pattern of profitability of technical stock market trading confirms that this in generally the case. The underlying pattern of upward and downward price runs that give rise to medium-term trends in the stock market is quite similar to the pattern observed in the foreign exchange market (this is seen below in the performance of the technical trading models). The «bull market» of 1982/87 was mainly brought about by the fact that the upward runs lasted longer on average than the counter-movements. Similarly, the «bear market» of 1973/74 was mainly due to the fact that the downward runs lasted longer on average than the upward runs[4]. The main difference between the two price series lies in the fact that price runs in the stock market last much shorter and are much steeper than exchange rate runs. It is for this reason that we analyze the profitability of technical trading in the stock market with both daily and hourly data. A comparison of Figure 2 with Figure 4 shows that the persistence of stock price runs becomes much clearer when hourly data are used rather than daily data.

3. The Profitability of Technical Analysis in the Foreign Exchange Market and in the Stock Market

a) *Some Characteristics of Technical Trading Systems.* The term «technical analysis» is a rather general heading for a myriad of trading techniques. These techniques attempt to derive profitable buy and sell signals by isolating systematic components in the behavior of a price series (see Kaufmann 1978 for an excellent treatment). There are two general approaches in technical analysis, one involves qualitative techniques and the other quantitative techniques. The qualitative techniques rely on the interpretation of some (purportedly) typical configuration of the ups and downs of price movements (e.g., head and shoulders, top and bottom, and Elliot Wave formations). They therefore contain an important subjective element. On the other hand, the quantitative techniques try to isolate runs from non-directional movements using statistical transformations. These techniques produce a clearly defined series of ex ante buy and sell signals. As such, they can be formally tested. The analysis below tests the efficacy of four types of objective trading rules: 1) moving average models; 2) momentum models; 3) the point and figure technique; and 4) filter rules.

The moving average models (MA) are one of the most widely used technical tools. They usually consist of one or two (unweighted) moving averages over the preceding days or hours. 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.

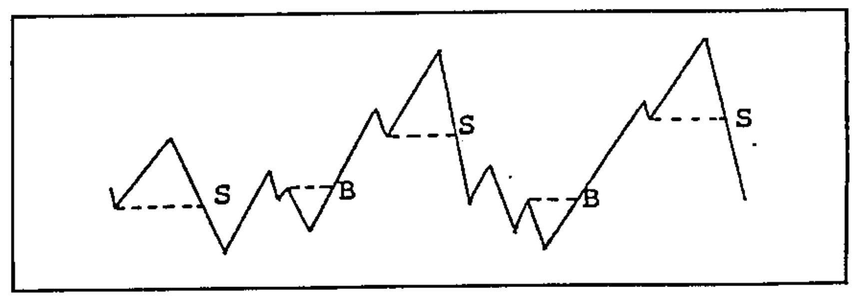
Note that when only one moving average is used, the spot price series serves as the short-term (one day or hour) moving average.

The momentum models and the point-and-figure technique are also widely used trading strategies. The momentum rule (M) is based on the first difference between the current price and that of K days (or hours) ago. The trading rule is as follows:

- Buy (go long) when the current price exceeds the price of K days ago and sell (go short) when the current prices falls below the price of K days ago.

The popular point-and-figure technique is in many respects a qualitative approach (Kaufman 1978). However, its basic trading rule can be programmed and is therefore objectively testable (it was originally developed by Dow):

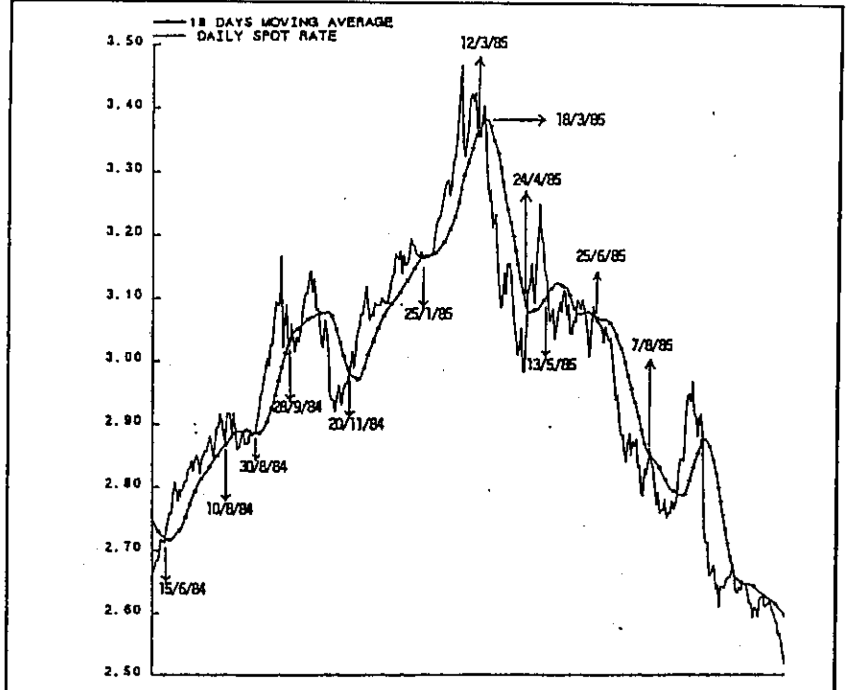
- Buy (go long) when a rising price exceeds the most recent high and sell (go short) when a falling price falls below the most recent low. A simple chart may clarify the meaning of this rule:



Finally, the filter rule prescribes the following strategy:

- Buy (go long) when the price exceeds the most recent low by X percent and sell (go short) when it falls below the most recent high by Y percent.

BUY AND SELL SIGNALS FOR THE DM/$ EXCHANGE RATE
(June 1984 - November 1985) Figure 3



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Filter rules are not considered a component of technical analysis in either theory or practice (Kaufman 1978 does not even mention them). Economists, however, have often used the filter rule to test for market efficiency (e.g., in the stock market see Alexander 1964 and Fama and Blume 1966; in the commodities market see Stevenson and Bear 1970; in the foreign exchange market see Poole 1967, Dooley and Shafer 1983, Logue and Sweeney 1977, Cornell and Dietrich 1978, and Sweeney 1986). We analyze the performance of several filter rules in order to test the relevance of these market efficiency tests.

Table 2 and Figure 3 demonstrate how a simple trading model performed between June 1, 1984 and November 29, 1985 (18 months around the peak level of the dollar exchange rate).

Table 2: Technical Trading Models: Moving Average

Buy and sell signals and rates of return on capital at risk
Price series: daily DM/$ exchange rate
Period: 1/6/1984-29/11/1985
Trading rule: moving average
Short term moving average: Length: 1 Lag: 0
Long term moving average: Length: 18 Lag: 9

Date	Signal	Days	Spot rate	Single rate of return	Total rate of return per year
1/6/1984	S	0	2.7100	.0	.0
15/6/1984	B	14	2.7292	— .7	— 18.4
10/8/1984	S	56	2.8770	5.1	23.1
13/8/1984	B	3	2.9172	— 1.4	15.3
16/8/1984	S	3	2.8590	— 2.0	4.9
28/8/1984	B	12	2.8914	— 1.1	— .4
29/8/1984	S	1	2.8803	— .4	— 2.0
30/8/1984	B	1	2.8863	— .2	— 2.8
28/9/1984	S	29	3.0240	4.6	11.8

Total rate of return per year: 16.0

Number of trading signals: 38; of which: buy signals: 19; sell signals: 19

Average duration of open positions: 14.8 days; of which: long positions: 15.1 days; short positions: 14.4 days

Sum of profits: 44.9 cents
Number of profits: 11
Average duration of profitable positions: 34.7 days
Average return from profitable positions: 4.08
Average return from profitable positions: per day .12

Sum of losses: — 20.9 cents
Number of losses: 26
Average duration of unprofitable positions: 6.3 days
Average return from unprofitable positions: — .80
Average return from unprofitable positions per day: — .13

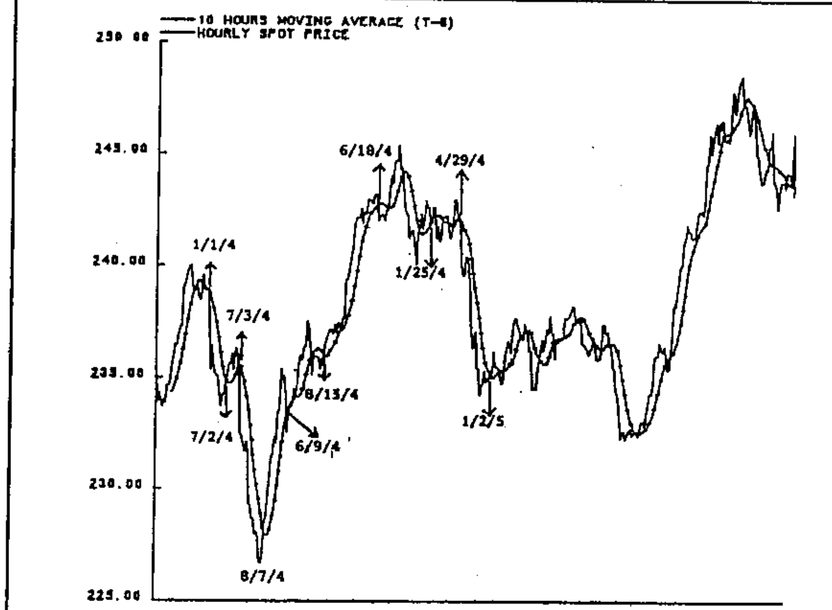
Annual rate of return from buying and holding: — 5.1%

This model is based on one 18 day moving average (in this case the original series serves as the short-term moving average). On June 15, 1984 one dollar was bought for 2.7292 DM and on August 8, 1984 it was sold for 2.8770 DM. This translates into a profit of 5.1 cents over a 56 day period[5]. The Figure and Table clearly demonstrate how this trading rule was able to exploit the persistence of the exchange rate runs irrespective of their direction (the most profitable trades are indicated in the chart). However, smaller fluctuations can cause the model to produce wrong signals (losses), particularly if there is no underlying upward or downward trend. Such whipsaws prevailed between May 13 and June 26, 1985. However, these single losses were all small precisely because the ups and downs were small. The overall profit from blindly following this trading rule over 18 months was 16.0 percent per year. A momentum model operating with a time span of K = 8 days produced an annual return of 33.3 percent and the Dow rule brought a 24.5 percent annual return.

Figure 4 and Table 3 demonstrate how a trading model, which consists of one 10 hour moving average, performed in the stock market between April 1st, 1986 and September 30, 1986 using hourly data on the S&P 500[6]. On April 1st at 9:00 a.m. (the first hour of trading) the model signalled a short position; thus, the S&P 500 stocks were sold at 238.92. The next day, at 3:00 p.m., the rule indicated that the stocks should be bought back at 235.1. Hence, the transaction yielded a single return of 1.6 percent over the two day period, or 1.6 cents if it is assumed that there is always one dollar in the game[7]. The third and fourth trades were also highly profitable, earning 2.9 and 1.7 cents respectively. But, between the opening hour on April 25th and noon on April 29th, a typical whipsaw movement took place, causing the rule to produce a sequence of 5 losses (see Figure 4). However, the exploitation of the following downward run which lasted until 9:00 a.m. on May 2nd resulted in a profit of 2.8 cents, much more than the 5 losses incurred during the whipsaw (1.7 cents). For the period as a whole, the moving average model produced a gross return of 23.3 cents, which translates into an annual profit rate of 46.5 percent.

BUY AND SELL SIGNALS FROM TECHNICAL TRADING MODELS S & P 500 (1986 March 25th- 1986 June 5th)

Figure 4



Source: AUSTRIAN INSTITUTE OF ECONOMIC RESEARCH

When moving average models are tested with daily stock price data over the same period, it was found that the most efficient daily model — one with a 2 day moving average — produced an overall return of only 10.2 percent, much less than the hourly model (46.5%). The reason for this difference lies in the inability of the daily data to capture the very brief but still significant intraday price runs. This is particularly clear since the length of the respective moving averages in «real» time — 2 days in one case and 10 trading hours in the other — is quite similar. Since price runs in the stock market are relatively short, the «fastest» models (i.e., the models that produce the maximum number of trading signals) were found to be the most profitable when based on daily data. The most profitable daily models involved, therefore, the shortest possible moving average in the case of the MA model (2 days) and the shortest

Table 3: Technical Trading Models: Moving Average

Buy and sell signals and rates of return on capital at risk
Price series: Standard & Poor's / hourly-data (8)
Period: 1/1/4/1984-8/30/9/1986
Trading rule: moving average
Short term moving average: Length: 1; Lag: 0
Long term moving average: Length: 10; Lag: 5

Date	Signal	Days	S & P 500	Single rate of return	Total rate of return per year
1/ 1/4/86	s	.0	238.92	.0	.0
7/ 2/4/86	b	1.8	235.10	1.6	333.5
7/ 3/4/86	s	1.0	235.35	.1	226.3
8/ 7/4/86	b	4.1	228.63	2.9	242.1
6/ 9/4/86	s	1.8	232.59	1.7	266.3
2/10/4/86	b	.5	234.59	−.9	217.3
3/10/4/86	s	.1	234.19	−.2	207.6
4/10/4/86	b	.1	234.73	−.2	195.9
5/11/4/86	s	1.1	235.21	.2	182.0
5/14/4/86	b	3.0	236.60	−.6	125.6
7/15/4/86	s	1.3	237.17	.2	120.9
8/15/4/86	b	.1	237.73	−2.	114.1
6/18/4/86	s	2.8	242.07	1.8	134.1

Total rate of return per year: 46.5

Number of trading signals: 115
Number of buy signals: 77
Number of sell signals: 78

Average duration of open positions: 1.2 days; of which: long positions: 1.3 days; short positions: 1.1 days

Sum of profits: 56.5 cents
Number of profits: 50
Average duration of profitable positions: 2.2 days
Average return from profitable positions: 1.13
Average return from profitable positions per day: .51

Sum of losses: −33.2 cents
Number of losses: 104
Average duration of unprofitable positions: .7 days
Average return from unprofitable positions: −.32
Average return from unprofitable positions per day: −.46

Annual rate of return from buying and holding: −6.2%

possible time span in the case of the momentum model (K = 1 day).

Tables 2 and 3 demonstrate that there are several features which are characteristic of technical trading systems, irrespective of whether they are used in the foreign exchange market with daily data or in the stock market with hourly data. First, the number of single losses is always greater than the number of single profits[8] and second, the overall profitability of the rules is due to the fact that the duration of profitable positions is much longer than the duration of unprofitable positions. This second point can be seen from the fact that the average return per day (i.e., the «slope» of the price movements) is roughly the same for both the profitable and the unprofitable positions. Note that this corresponds precisely to the general pattern of speculative prices observed in Section 2, i.e., the dynamics of speculative prices consist of many small fluctuations and fewer relatively persistent runs. As a consequence, the distributions of the single rates of return both have the following properties: the medians are negative and the means are positive, the distributions are therefore skewed to the right and the coefficients of kourtosis are greater than that of a normal distribution.

The riskiness of technical noise trading can be estimated by testing the mean of the single rates of return against zero using the t-statistic (only if the mean is negative does the trading rule produce an overall loss)[9]. The probability of incurring an overall loss by following the trading rules examined in this study was found to be below 5% generally; in many cases this figure was below 1 percent[10].

b) *The Performance of Technical Trading Systems in the 1970s and 1980s.* Table 4 shows how some selected technical trading models performed in the foreign exchange market between April 2, 1973 and October 1, 1986 (as well as during 9 sub-periods of 18 months). All of these trading rules produced substantial gross returns in every sub-period, though at a varying rate. The annual return over the whole period centered on 15 percent, far above the zero return that would be expected in an efficient market. Two of the models, which combine the trading rule of the moving average and the momentum model (MA&M rules) performed the best (in this case a trade is executed only if both techniques signal the same — long or short — position). It is therefore not surprising that the model that «Citicorp», the most important single participant in the foreign exchange market, developed for its foreign exchange activities is of this combined type (the profitability of this model — called «Citi-trend» — is discussed in Schulmeister 1987). In all, 18 trading models were found which produced substantial gross returns during the entire period between April 1973 and September 1986, as well as during each of the 9 sub-periods (8 moving average models, 2 momentum models, 7 models which combine both rules and the Dow rule).

It is interesting to note that the filter rule performed poorly relative to the other trading systems. No filter could be found which was consistently profitable, the best produced losses in two sub-periods. The main reason for the relative poor performance of the filter rules lies in the fact that this rule was more sensitive to variations in the parameters and/or changes in the actual pattern of the price series than the traditional technical trading systems. Table 4 also shows how the selected technical models performed between October 1986 and March 1988. Most of the trading techniques remained profitable, though less so than in the preceding years. This reduction in the profitability of short-term currency speculation can be traced to the stabilizing effects of the Louvre accord of February 22, 1987. Until then, all of the trading rules produced profits, some were extremely profitable. However, after the Louvre accord was settled by the Group of Seven, the rates of return of the selected trading rules fell significantly, three of them even produced losses.

Table 5 shows how the «fastest» daily trading models performed in the stock market between January 1, 1970 and June 30, 1987, as well as during two larger sub-periods (1970/78 and 1979/87) and 6 smaller sub-periods, each lasting 3 years (1987 includes only the first two quarters). All of these daily models were found to be highly efficient, not only during the overall period but during most of the sub-periods as well. This result holds true for the two indices examined, the S&P 500 and the

Table 4: Annual Rates of Return from Following Trading Rules for the DM/$ Exchange Rate

Date or period	Moving average		Momentum		Moving Average & Momentum		Point & Figure (Dow Rule)	Buy & Hold Dollars
	MAS: 3 MAL: 10	5 10	K: 8	10	MAS: 3 MAL: 10 K: 10	5 10 10		
2/ 4/1973								
	24.1	35.3	31.1	29.1	32.9	35.6	23.8	— 5.1
1/10/1974								
	14.3	12.6	14.3	13.0	14.9	10.2	10.8	— 3.1
1/ 4/1976								
	4.1	4.1	2.8	5.5	4.3	6.1	3.7	— 6.9
3/10/1977								
	8.2	13.7	1.2	11.3	10.3	9.8	9.6	—14.6
2/ 4/1979								
	16.6	16.9	12.6	13.7	15.0	16.4	13.5	— 2.7
1/10/1980								
	11.0	8.1	1.5	5.4	4.6	9.8	5.5	16.7
1/ 4/1982								
	10.2	9.9	12.2	16.1	11.4	10.2	12.1	5.4
3/10/1983								
	28.2	30.0	32.1	27.3	30.6	24.2	27.0	10.2
1/ 4/1985								
	12.2	5.8	12.2	18.4	19.1	19.0	15.5	—35.0
1/10/1986								
2/4/73-1/10/86	14.3	15.1	13.3	15.5	15.9	15.7	13.5	— 3.0
1/10/1986								
	34.5	14.6	23.8	2.9	12.9	12.9	51.5	—27.6
20/2/1987								
	0.2	— 2.4	—12.0	6.2	5.6	4.4	— 2.4	— 9.3
31/3/1988								
1/10/86-31/3/88	9.0	2.1	— 2.7	5.4	7.5	6.6	11.5	—14.8

Table 5: Annual Rates of Return from Following Trading Rules for Daily Stock Price Indices

	Filter	Moving average	Momentum	Point & Figure (Dow Rule)	Buy & Hold
	X: 0.1 Y: 0.1	MA: 2	K: 1		
		S&P 500:			
1970/87[1]	24.5	24.8	24.8	7.7	7.0
1970/78	33.5	34.8	36.0	14.1	0.4
1978/87[1]	15.1	14.4	13.0	1.0	14.4
1970/72	32.9	35.2	37.6	15.3	8.3
1973/75	44.4	42.3	46.4	21.1	−8.9
1976/78	22.8	26.5	23.6	5.8	1.9
1979/81	22.9	16.6	22.7	−2.3	8.2
1982/84	5.8	10.3	2.1	1.9	10.9
1985/87[1]	17.3	17.1	14.8	4.2	27.7
		Dow Jones:			
1970/87[1]	22.6	25.2	21.9	8.1	6.5
1970/78	34.8	25.6	33.7	14.3	−0.1
1978/87[1]	9.8	14.3	9.5	1.4	13.7
1970/72	33.8	33.7	34.3	18.7	8.0
1973/75	50.2	49.8	50.8	14.6	−6.2
1976/78	20.6	23.3	16.1	9.0	−2.1
1979/81	10.5	16.4	7.9	9.0	2.5
1982/84	8.6	18.6	10.4	−2.6	11.2
1985/87[1]	10.6	6.9	10.4	−3.1	32.6

[1] Sample period ends June 30, 1987.

Dow Jones 30 Industrials. The annual gross returns generated by the filter, moving average and momentum models were centered at 25 percent, with the t-statistic for the mean of the single returns exceeding 5.0 in all cases. Thus, the probability that the true mean is zero or less is below 0.005 percent. Only the point and figure rule (the Dow Jones rule) produced minor losses in three of the smaller sub-periods.

The analogous results for the hourly technical models are presented in Table 6[11]. The annual rates of return are generally much greater. The average return over all of the sample periods and over all of the 9 selected models is 60.4 percent with the S&P 500 price series and 54.0 percent with the Dow Jones price series. Note that the Dow role performed relatively well with hourly data (whereas with daily data this rule performed relatively poorly). The difference in overall returns between the hourly and daily models is explained by the fact that the hourly models are able to identify and exploit the short but significant price runs much more efficiently than the daily models (a 15 minute model would probably perform still better). The frequency of these short but significant price runs, which often occur within the same trading day, has increased strongly over the last 17 years. This is seen by observing that the numer of trading signals produced by the same types of hourly models has increased significantly over time, particularly in the 1980s (this phenomenon is documented in Goldberg and Schulmeister 1988). One of the consequences of this greater short run price behavior is that it has contributed to a decline in the efficacy of the daily models over time (see Table 5). This occurs because these models continually find themselves lagging significantly behind the optimal buying and selling prices[12]. Note that the higher rates of return produced by the hourly models are consistent with the results of the random walk tests, namely, that the random walk tends to be more strongly rejected as the frequency of the data is increased (see footnote 4). Table 6 also presents the performance of two models that combine the moving average and momentum rules (MA&M rules). Both models are only slightly less efficient than the other trading rules, but due to the combined effect of the two rules the number of trading signals is significantly reduced. Thus, the MA&M rules provide a way to substantially reduce the cost of transacting without substantially sacrificing overall performance.

It is interesting to note that when employed in the stock market the filter rule was no less efficient than the traditional technical systems (although less consistently so). This holds true for daily data as well as for hourly data (see Tables 5 ad 6). This result confirms the findings of an earlier study on stock

Table 6: Annual Rates of Return from Following Trading Rules for Hourly Stock Price Indices

	Filter		Moving average		Momentum		Moving average & Momentum		Point & Figure	Buy & Hold
	X: 0.1 Y: 0.1	0.3 0.3	MA: 8	10	K: 5	7	MA: 8 K: 7	10 5		
				S&P 500:						
2nd + 3rd Quarter										
1971	76.5	26.5	50.0	37.2	52.6	43.6	35.7	40.2	58.4	— 3.8
1974	106.9	138.8	126.9	114.3	122.4	103.8	110.9	110.2	130.6	— 54.3
1977	60.6	32.8	51.4	54.2	47.9	31.0	31.4	50.9	40.3	— 4.8
1980	81.0	60.6	64.4	56.4	64.1	38.7	46.7	53.4	57.8	49.1
1983	35.8	53.4	44.3	46.6	55.0	39.3	41.3	45.5	41.0	18.9
1986	60.8	49.9	55.8	46.5	55.3	42.5	39.0	38.2	63.7	— 6.2
Average Rate of Return	70.3	60.3	65.5	59.2	66.2	49.8	50.8	56.4	65.3	— 0.2
				Dow Jones:						
2nd + 3rd Quarter										
1971	66.6	17.9	45.8	39.1	34.8	48.1	43.5	35.2	62.6	— 3.9
1974	162.6	116.6	121.1	124.5	95.2	103.9	100.5	102.0	104.0	— 48.4
1977	71.9	31.1	51.8	37.8	38.7	43.6	38.5	30.3	22.8	— 15.4
1980	81.2	71.8	56.5	48.2	63.5	31.3	37.5	47.2	66.9	40.5
1983	3.5	27.6	35.8	38.6	24.0	48.5	44.4	32.7	16.2	20.4
1986	18.8	39.8	41.8	46.2	40.4	36.8	42.6	42.7	40.7	— 5.9
Average Rate of Return	67.4	50.8	58.8	55.7	49.4	52.5	51.2	48.4	52.2	— 2.1

Table 7: Pattern of Profitable DM/$ Trading
(Period: 2/4/1973 - 1/10/1986)

	Moving Average MAS: 5 MAL: 10	Momentum K: 10	Moving Average & Momentum MAS: 3 MAL: 10 K: 10	Point & Figure (Dow Rule)
Annual rate of return	15.1	15.5	15.9	13.5
Sum of profits per year (cents)	25.1	25.6	23.4	25.7
Profitable positions				
Number per year	9.5	12.7	7.5	10.9
Average return				
Per position	2.65	2.01	3.12	2.36
Per day	0.09	0.09	0.08	0.11
Average duration in days	28.6	22.0	37.6	22.4
Sum of losses per year (cents)	— 10.0	— 10.1	— 7.5	— 12.3
Unprofitable positions				
Number per year	11.3	16.4	9.0	17.4
Average return				
Per position	— 0.88	— 0.61	— 0.84	— 0.70
Per day	— 0.11	— 0.12	— 0.09	— 0.10
Average duration in days	8.3	5.2	9.4	7.0
Single rates of return				
Mean	0.73	0.53	0.97	0.48
Median	— 0.14	— 0.09	— 0.14	— 0.24
S.D.	2.67	2.25	3.01	2.11
Skewness	2.41	3.41	2.26	2.14
Kurtosis	12.99	24.03	10.90	9.07
t-statistic	4.56	4.69	4.78	4.40

market efficiency (Fama and Blume 1966). This earlier study found that when based on gross returns, the smaller filters outperformed the buy and hold strategy with daily data.

c) *The Pattern of Profitability of Technical Trading Systems.* Tables 7, 8 ad 9 elaborate upon the pattern of profitability over

Table 8: Pattern of Profitable Stock Market Trading Based on Daily Data
(Period: 1/1/1970 30/6/1987)

	Filter X: 0.1 Y: 0.1	Moving Average MA: 2	Momentum K: 1	Point & Figure (Dow Rule)
		S&P 500		
Annual rate of return	24.5	24.8	24.8	7.7
Sum of profits per year (cents)	64.9	61.4	67.1	31.7
Profitable positions				
Number per year	42.4	38.9	46.0	11.4
Average return				
Per position	1.53	1.58	1.46	2.77
Per day	0.26	0.25	0.28	0.14
Average duration in days	5.8	6.4	5.2	20.2
Sum of losses per year (cents)	– 40.4	– 36.5	– 42.3	– 24.0
Unprofitable positions				
Number per year	56.2	49.0	64.5	17.5
Average return				
Per position	– 0.72	– 0.75	– 0.66	– 1.37
Per day	– 0.34	– 0.32	– 0.34	– 0.18
Average duration in days	2.1	2.4	1.9	7.7
Single rates of return				
Mean	0.25	0.28	0.22	0.27
Median	– 0.17	– 0.15	– 0.11	– 0.50
S.D.	1.54	1.63	1.47	2.96
Skewness	1.39	1.78	1.51	2.29
Kurtosis	7.18	9.36	8.44	10.96
t-statistic	6.68	6.79	6.70	2.03

the entire sample period in both markets by splitting the sum of profits (losses) into three components, namely, the number of profitable (unprofitable) positions, their average duration in days and the respective return per day (note that the product of these three components yields the sum of profits or losses). The tables illustrate that the pattern of returns which was found for the two small sub-periods (Tables 2 and 3) represents a general pattern underlying the efficacy of all of the technical trading systems. The number of losses is always greater than the number of profits and the average profit (loss) per day is roughly equal for profitable and unprofitable positions. The overall profitability, therefore, is due to the fact that the average duration of the profitable positions is approximately 3 to 4 times longer than that of the unprofitable positions. This phenomenon is the result of the systematic exploitation of the pattern of price runs already discussed. Since most of these price runs are rather short, the greatest part of any overall price change is brought about by few longer lasting runs[13]. The smaller fluctuations often cause technical models to produce losses, wich, however, are small precisely because the fluctuations are small. The profits from the correct identification and exploitation of the few but persistent price runs, which change speculative prices the most, can, therefore, easily compensate for the more frequent and much smaller losses stemming from the minor fluctuations («whipsaws»). The distributions of the single rates of return in the two markets reflect these observations. The medians are negative and smaller than the means, and both distributions are leptokurtotic.

Although the pattern of profitability is similar in the two markets, a comparison of Table 7 and 8 shows that the performance of the daily trading systems, and thus the underlying pattern of price movements, does differ quantitatively between the foreign exchange market and the stock market. The number of profitable and unprofitable positions is roughly 4 times higher in the stock market than in the foreign exchange market for the same type of trading systems. Consequently, open positions last approximately 4 times longer when the trading is done in the DM/$ market. This difference can be traced to the fact that price runs are much shorter in the stock market than in the foreign exchange market. At the same time, stock price movements are much steeper than exchange rate movements. Consequently, the average return per day is roughly three times higher in the stock market (roughly 1.5 cents). Thus, the difference in the average return from profitable positions in the stock market (roughly 1.5 cents) and in the foreign exchange market (roughly 2.5 cents) is only 1 cent. The average losses from unprofitable positions differ by an even lesser amount.

The preceding observations, then, indicate rather clearly that the higher overall profitability of technical trading in the stock market relative to the foreign exchange market stems partly from the fact that in the stock market the rules involve higher turnover. The higher turnover more than compensates for the lower return per transaction[14]. In addition, the specific «speed» of the stock market explains why the hourly models performed much better than the daily models (compare Tables 8 and 9). The small difference in the average return of profitable positions from hourly and daily models is due to the steeper «slope» of hourly price runs, i.e., the higher return per day of hourly runs almost completely compensates for their shorter duration. The losses from unprofitable positions is at the same time significantly smaller for hourly models. Hence, the combined effects of higher turn-over and a steeper slope with hourly models in the stock market result in a much higher overall profitability relative to the daily models in the foreign exchange market.

Finally, it can be seen in Table 9 that although the rates of return of the hourly models are fairly uniform over the subperiods (except for the return in 1974), the pattern of profitability seems to have changed significantly, particularly since 1980. Since then, the hourly models have signalled an increasing number of trades, which, however, are producing a larger number of single losses than before 1980. At the same time, the return per day from profitable positions, and thus the slope of the persistent price runs, has increased, so that the overall rate of return has diminished only slightly. However, the t-statistic of the single rates of return has declined (due to the decreasing mean of the single returns). This suggests that stock market trading based on hourly data has become riskier in the 1980s. These changes in the pattern of profitability are typical for all of the hourly trading models examined (see Goldberg and Schulmeister 1988). These findings indicate that stock price runs have become shorter and steeper in recent years and that the number of smaller fluctuations (whipsaws) has increased significantly. One can presume, therefore, that models using higher fre-

Table 9: Pattern of Profitable Stock Market Trading Based on Hourly Data
Trading Rule: Moving Average & Momentum [MA:8/K:7]

	1971	1974	1977	1980 2nd & 3rd Quarter	1983	1986
			S&P 500			
Annual rate of return	35.7	110.9	31.4	46.7	41.3	39.0
Sum of profits per year (cents)	62.4	153.8	55.6	96.2	89.4	103.6
Profitable positions						
Number per year	70	76	70	66	72	80
Average return						
Per position	0.89	2.02	0.79	1.46	1.24	1.30
Per day	0.25	0.51	0.20	0.37	0.36	0.48
Average duration in days	3.6	4.0	3.9	4.0	3.5	2.7
Sum of losses per year (cents)	−26.6	−42.6	−24.0	−49.4	−48.8	−64.6
Unprofitable positions						
Number per year	84	66	72	96	105	168
Average return						
Per position	−0.32	−0.65	−0.33	−0.51	−0.44	−0.38
Per day	−0.23	−0.69	−0.26	−0.47	−0.44	−0.43
Average duration in days	1.4	0.9	1.3	1.1	1.0	0.9
Single rates of return						
Mean	0.23	0.78	0.22	0.29	0.22	0.16
Median	−0.06	0.05	−0.01	−0.19	−0.12	−0.20
S.D.	0.82	1.99	0.83	1.20	1.15	1.11
Skewness	0.80	1.65	1.34	1.22	1.84	2.57
Kurtosis	5.05	5.81	5.52	3.93	6.87	11.72
t-statistic	2.46	3.29	2.22	2.15	1.84	1.58

quency data, such as 15 or even 5 minute models would perform still better than hourly trading systems (for the same reasons why hourly models performed much better than daily models).

4. Transaction Costs and the Role of the Futures Market

The costs associated with using the trading systems examined in this study differ considerably whether one is trading currency or stock. In the foreign exchange market these costs stem from two factors: 1) the bid-asked spread; and 2) the interest rate differential between dollar and deutschemark eurodeposits. The costs due to the first factor are estimated to be a maximum of 0.02 percent per trade[15]. Thus, the four trading rules listed in Table 7, wich produced an average of 47 trades per year (the annual number of profitable and unprofitable position was 23.7 on average), involved transaction costs of less than 1 percentage point per year on average[16].

The potential costs due to the interest rate differential are also of a negligible magnitude[17]. In the years that involved a depreciating dollar the net interest rate effect was negative, since in these periods the duration of long positions was shorter than the duration of short positions. (Note that the dollar interest rate exceeded the deutschemark interest rate in all years save 1973). The opposite was true in the years 1980 to 1984 (and also 1975), when the interest rate effect was positive and increased the profitability of technical currency trading. The total interest rate effect over the 13.5 year period was, therefore, practically nil (see Schulmeister 1987). This implies that net returns can be obtained by subtracting one percentage point from each figure presented in Table 7. Hence, when adjusted for all of the costs associated with transacting, the return from technical trading in the deutschemark-dollar market remains considerable.

In terms of the cash market for stock, the costs associated with technical trading are higher than they are in the foreign exchange market because such trading involves not only a larger number of trades, but higher costs per trade[18]. These costs consist mainly of two components: 1) commissions; and 2) slippage costs (slippage costs are incurred when prices move unfavorably after the price signal arrives but before the trade is executed)[19]. In addition, the magnitude of both cost factors depends on whether or not a trader is member of the NYSE. For a non-member, Stoll and Whaley (1987) estimate that on a trade of $10 million of S&P 500 stocks, commissions and slippage costs are $17,500 (based on $.07 per share) and $25,000 respectively. This translates int a total cost of 0.42 percent per trade. Thus, the hourly MA&M (MA:8/K:7) rule, which generated an average of 344 trades per year (Table 9), involved an annual cost of 144.5 percent on average. Given that the MA&M (MA:8/K:7) rule produced a return of 50.8 percent on average (Table 9), the cost associated with using this rule to trade the S&P 500 stocks was therefore prohibitive for a non-member.

For members of the NYSE both cost factors are considerably lower than for non-members. Goldberg and Schulmeister (1988) estimate commission costs (mainly clearing house and exchange fees) to be 0.025 percent per trade. This implies, given the figures in Table 9, a break-even level of slippage costs of $12,267 for members using the MA&M (MA:8/K:7) rule to trade $10 million of S&P 500 stocks; with the Dow Jones 30 stocks this figure was $10,429. Thus, with slippage costs below these break-even levels the MA&M (MA:8/K:7) rule would have been profitable. For example, with average slippage costs of $7,500 per transaction, the leveraged net return on using this rule to trade the Dow Jones 30 stocks would have been 58.0 percent annually[20]. There are, however, two reasons to suspect that actual slippage costs in the cash market are probably above the break-even levels. First, there is a NYSE rule which prohibits short sales on a down tic, i.e., short sales can only be executed if the price of the preceding transaction involves either a zero or positive price change. Second, delivery is mandatory on the NYSE and, as a result, a short seller must find a dealer holding a sufficiently diverse and large basket of stocks who is willing to lend them. Both of these factors cause slippage costs to be larger than they would be otherwise. Hence, although the results of the trading rule tests reveal that past prices do contain information relevant for predicting future price movements, operating procedures peculiar to the NYSE may preclude the profitable use of such information.

In terms of noise trading on the CME, the results are much clearer[21]. The CME provides a much more conducive environment for noise trading. This stems not only from the fact that the costs of trading are lower, but it is also because the CME allows futures contracts to be bought on a 10 percent margin. Stoll and Whaley (1987) estimate that for non-members of the exchange, commissions and slippage costs both amount to $12.50 each per $100,000 contract (assuming an index of 200.00) or 0.025 percent per trade. Based on 344 trades per year (the MA&M, MA:8/K:7 rule), the total annual cost due to these factors was 8.6 percent per contract for non-members on average. Even the other trading systems presented in Table 6 (except the filter rule) all involved costs under 20 percent per year (the filter rule produced up to 1200 trades per year which implies transaction costs of 30 percent). Hence, all of the technical rules listed in Table 6 (when based on the S&P 500 price series) were highly profitable, since no rule (except the filter rule) produced a leveraged net return of less than 250 percent in any of the periods examined since the CME began trading S&P 500 futures contracts. These trading rule results suggest rather strongly that the market for equities, in the broader sense, is characterized by economically significant departures from market efficiency.

The importance of stock index futures markets for noise trading cannot be overemphasized. The low transaction and information costs associated with their use as well as the ease and speed with which they enable traders to jump back and forth between long and short positions combine to make these markets the ideal medium in which to implement technical trading strategies, especially those outlined in this study[22]. The phenomenal growth in the trading of index related futures contracts since their introduction in 1982 and 1983 is in large part related to the use of technical analysis as well as portfolio insurance and program trading[23]. This can be seen from the fact that daily turnover in the S&P 500 futures market (traded contracts per outstanding contracts) fluctuates between 0.5 and 1.0 (see any recent issue of the «Wall Street Journal»), implying that open positions last on average 1 to 2 days. This mirrors exactly the trading behavior implied by the hourly trading systems[24]. The Katzenbach study concludes (as reported in the December 31, 1987 issue of the «New York Times») that

> ...The stock-index futures market... is by nature shorter-term and thus more speculative. ...Stock-index futures can be used to hedge holdings of stocks... but this function is hardly as significant as advocates of the futures markets urge. In short, stock-index futures are attractive because they are a cheaper way to play the market[25].

Although it is generally acknowledged that the presence of noise traders is large, their influence on futures prices and, through index arbitraging on cash prices, in generally overlooked. The two unprecedented episodes of declining prices that occurred in the markets for equities on September 11 and 12, 1986 and October 19 and 20, 1987 have generally been attributed to market fundamentals and the presence of portfolio insurers and index arbitragers[26]. The importance of noise trading for these two events has gone largely unnoticed. The next Section addresses this issue by examining the use and profitability of technical analysis during the period surrounding the crash of October 19, 1987.

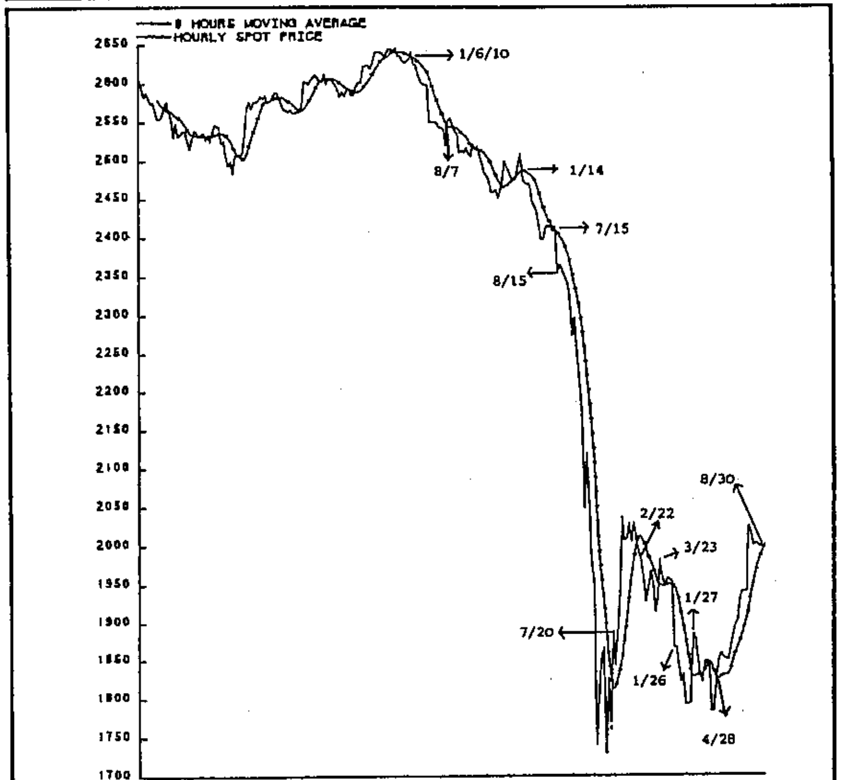
5. The Stock Market Crash of October 19, 1987: An Out-of-Sample Case Study

On October 19, 1987 the Dow Jones Industrials dropped 508 points (23 percent) on an unprecedented volume of 604 million shares and during the following day, October 20th, the entire financial system came close to collapsing. By most accounts a large portion of the blame for the events which transpired on October 19th centers on the activities of the index arbitragers and portfolio insurers[27]. But the arbitrage-insurance scenario, which at times can be a powerful engine for moving prices, does not provide a complete explanation for the events which transpired on October 19th and 20th. This is so for two reasons. First, it abstracts from the reasons behind the initial movements in futures prices to levels substantially below the arbitrage equilibrium value. Second, there is no explanation for why the disparity in spot and futures prices should persist and perpetuate the downturn despite heavy futures buying by index arbitragers. Thus, the arbitrage-insurance cycle represents only one piece of the puzzle. An examination of the profitability of noise trading and its significance for price movements indicates that such activity represents another piece of the same puzzle.

Figure 5 shows how a simple moving average model performed during the turbulent period between mid September and the end of October, 1987 using the hourly Dow Jones price series[28]. Prior to October 6th the model produced relatively «modest» returns of 29.6 percent. But during the next 8 days the trading rule was able to exploit 3 runs, pushing the total rate of return up to 93.7 percent by 3:00 p.m. on Thursday October 15th. At the close on Thursday a short position was signaled. This was the last trading signal to be produced before October 19th and it came more than one full trading day before the big event, during a time when buyers were easily found. Thus, the moving average model produced an enormous profit of 19.9 cents by signalling a sale at 2355.09 (on October 15th at 4:00 p.m.) and a subsequent purchase at 1886.44 (on October 20th at 3:00 p.m.). The following upward run, which occurred between October 20th and 22nd, also brought high profits, but because hourly data are too coarse to fully capture the intraday price movements (see Figure 5) the profit of 5.4 cents underestimates the profit actually obtainable with higher frequency data. Despite this bias towards underestimation, the profitability of the moving average model is quite remarkable. The rule produced and annual rate of return of 217.6 percent (unleveraged) over the sample period.

The other models listed in Table 6 were also tested for this period (save the filter rule) and all were found to be highly profitable. Their overall gross return (unleveraged) stood between 181.5 percent (the MA&M MA:10/K:5 rule) and 245.9 percent (the momentum K = 7 rule). All of the models signaled a short position more than one full trading day before the crash,

BUY AND SELL SIGNALS FROM A TECHNICAL TRADING MODEL AND STOCK MARKET TURBULANCES DOW JONES (1987 September 16th - 1987 October 30th) Figure 5



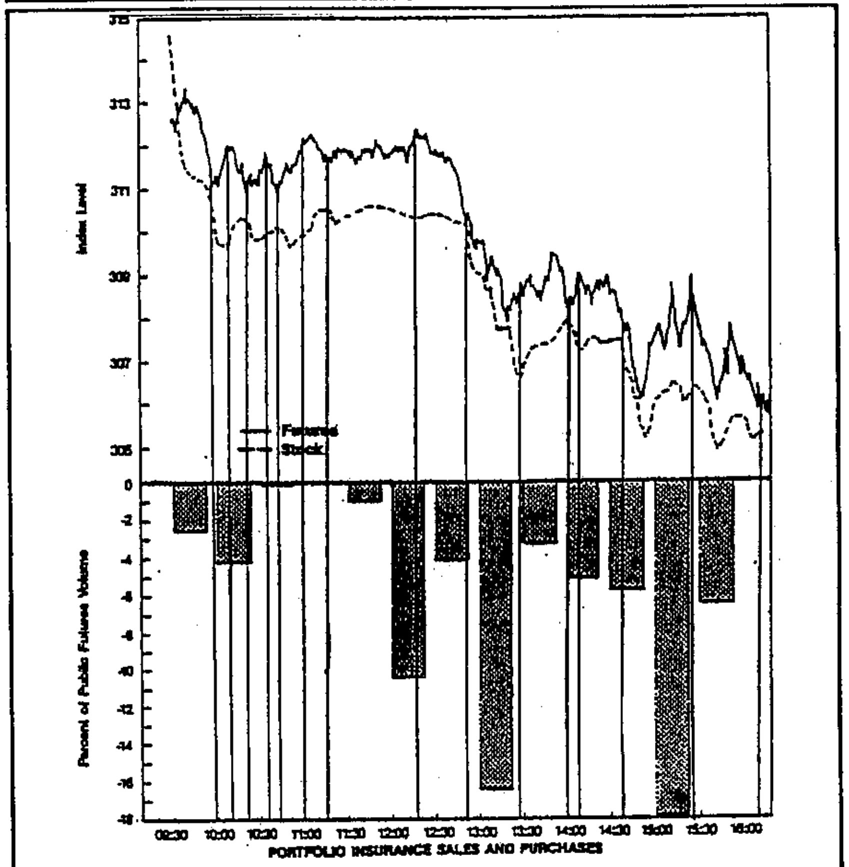
Source: AUSTRIAN INSTITUTE OF ECONOMIC RESEARCH

between 9:00 a.m. on October 14th and 4:00 p.m. on October 15th. Not surprisingly the Dow dropped a record (at that time) of 95.46 points on October 14th and 57.6 points on October 15th. This confluence of trading signals illustrates rather clearly the self-feeding nature inherent in the use of technical analysis. This self-feeding nature stems from the fact that the use of technical analysis is trend-reinforcing. As traders begin to act according to a particular technical model their behavior works to strengthen the persistence of the current run. This causes other traders, with slower models, to follow suit. The strength of this feedback mechanism and the impact on market prices increases as the use of technical models becomes more widespread.

Of course technical models are reactive, distinguishing trends only after they have begun. Consequently, the strong initial downward movement in prices which occurred on October 14th was caused by factors other than noise trading. According to most accounts (see the Brady Report) the overriding news event which occurred on that day was the report of an unexpectedly high trade deficit for the month of August, totaling $15.68 billion[30]. As this trade figure flashed across computer screens early in the morning on the 14th it caused a wave of selling to break out. But the selling pressure was greater in the futures markets, causing the spread between the futures and spot prices to decline substantially. In fact, this phenomenon of greater selling pressure in the futures markets and declining spreads (frequently pricing futures at a discount) was to repeat itself on many occasions during the remaining hours of trading on October 14th, as well as on the following two trading days. This futures market activity, then, led to substantial index arbitrage activity throughout this period and provided the impetus for the arbitrage-insurance cycle that took hold of the market.

In order to analyze the specific interaction of the futures and spot markets in the days before the crash it is useful to view one minute charts depicting price movements in both markets (Figure 6 displays one minute S&P 500 price movements for Wednesday, October 14, 1987)[31]. The Figure shows that the overall decline in price in both markets was brought about in a sequence of steep downward runs. These price runs, however, were triggered off invariably in the futures market. They were then transmitted to the spot market via index arbitraging with a lag of approximately 5 to 10 minutes. As a consequence, the spread between futures and spot prices narrowed during the initial downward runs in the futures market and reached a local minimum at the end of these runs far below the equilibrium value (according to The Presidential Task Force... 1988, p. II-7, the equilibrium spread was roughly 1.75 index points during the week prior to the crash). Once the selling pressure in the futures market expired, continued index arbitraging (the buying

S & P INDEX AND FUTURES CONTRACT
(Wednesday, October 14th 1987) Figure 6



Source: THE PRESIDENTIAL TASK FORCE ON MARKET MECHANISMS (1988), FIGURE 13

of futures and the selling of stocks) restored the equilibrium spread. On the upside, there were several occasions when upward runs in the futures market also led to a widening of the spread far beyond the equilibrium level (particularly on Thursday, October 15, 1987). Hence, the spread between futures and spot prices invariably reached a local minimum at the end of downward runs in the futures market and a local maximum at the end of upward runs in the futures market (see Figure

6). At the same time, the local minima of the spread were, without exception, much lower than the equilibrium level, while the local maxima of the spread exceeded the equilibrium level on several occasions (see Figure 6). This overshooting pattern is typical for the price movements on all three days prior to the crash, as well as on Black Monday (see the Figures 13, 15, 16, 18, 19, 21, 22, 24 in the Presidential Task Force... 1988).

In order to understand the specific price dynamics which ultimately led to the crash on October 19, 1987 it is important to determine which group of agents in the futures market was responsible for the frequent overshooting of the equilibrium spread. It was this frequent overshooting of the equilibrium spread which caused the index arbitragers to step in and continually push cash prices down, leading portfolio investors to sell futures and causing the conditions necessary for the arbitrage-insurance cycle to take root[32]. The SEC (1987) study on the earlier downturn of September 11 and 12, 1986 reports:

> Based on the data now available, the Division cannot fully explain the continued discount. Nevertheless, stock index arbitrage and substitution during this period involved predominantly the buying of futures, and this buying clearly exceeded sales associated with portfolio insurance. Therefore, the data suggest that program activity tended to support futures prices on September 11-12, and that factors other than arbitrage, portfolio insurance, index substitution, and other «program trading strategies» were largely responsible for the futures discounts observed on those days[33].

Although portfolio insurers have received much criticism, they cannot be blamed for the observed overshooting price runs in the futures market for two reasons. First, during the days before the crash, as well as on Black Monday, virtually no portfolio insurance purchases occurred (i.e., long futures), so that the existence of those few upward runs which let do a widening of the spread beyond the equilibrium value cannot be explained by these activities. Second, there is no clear relationship between downward runs in the futures market and portfolio insurance sales (see Figure 6 as well as figures 16, 19 and 22 in The Presidential Task Force... 1988). A majority of the downward runs which occurred on Wednesday, October 14th, for example, took place when the selling by portfolio insurers was rather modest (with the exception of the run that occurred between 13:00 hrs and 13:30, which, however, had already taken off around 12:40, when selling activity by portfolio insurers was relatively small). Moreover, when portfolio insurance sales reached their maximum for the day (between 15:00 and 15:30) prices in the futures market, rather than falling, increased strongly, leading to the maximum spread for the day (almost 3 index points).

Although the evidence is indirect, it seems reasonable to conclude, given the results of this study (i.e., the enormous profitability of all of the hourly rules as well as the confluence of trading signals during the week prior to October 19th) that noise trading was at least partly responsible for the overshooting price movements in the futures market. By pushing futures prices down relative to spot prices in short but persistent runs, noise traders inadvertently worked to trigger off the arbitrage-insurance cycle which took hold of the market on Black Monday. It seems, therefore, that noise trading was destabilizing and highly profitable at the same time.

6. Concluding Remarks

This paper provided an empirical and mainly inductive investigation into the dynamics of speculative prices using exchange rates and stock prices. We found that speculative prices in the short run move in a sequence of persistent upward and downward runs, which are interrupted often by non-directional fluctuations. Although this pattern is typical for both exchange rates and stock prices, there are important quantitative differences between these two price patterns, i.e., runs in the stock market last much shorter and are much steeper than exchange rate runs. The trading rule tests revealed that the short-term price dynamics in both markets can be exploited systematically by a wide array of technical trading systems. We thus concluded that both the foreign exchange market and the stock market (in the broader sense) were weakly inefficient. The analysis was also extended in an out-of-sample case study that focused on the profitability of using the rules to trade stock during the period surrounding the market crash of October 19, 1987. We found that the trading rules were even more profitable here than during the in-sample period and provided indirect evidence suggesting that technical noise trading played a significant role in causing the market collapse.

The preceding findings were found to hinge critically on several factors. The result of profitable technical noise trading in the foreign exchange market was based on the performance of the more widely used technical rules rather than the rarely used filter rule, the latter providing an unprofitable strategy in which to trade currency. In the market for stock, the profitability of technical noise trading was found to depend on the use of both hourly data and low cost futures contracts, i.e., the rules were found to be much less efficient with daily data and most likely unprofitable in the cash market for stock. Hence, the results of this study explain why the results of earlier trading rule studies in the foreign exchange market and the stock market generally support the efficient markets hypothesis, since for the most part these earlier studies examine only one type of trading model (the filter rule), use daily and lower frequency data and ignore the importance of futures contracts (see footnote 2).

Finally, the analysis found that medium-term trends of rising or falling prices are brought about by the fact that the many single price runs that constitute a medium-term trend last longer in one direction than in the other on average for several years. This phenomenon suggests that a medium-term expectational bias in favor or against a particular asset operates in speculative markets. When a positive bias prevails (i.e., a «bull market»), traders hold long positions some days longer than short positions on average, leading to an overall price rise in a step wise process (the opposite occurs in the case of a negative expectational bias, i.e., a «bear market»).

The findings of this study present at least three puzzles for further research: 1) Who are the losers in the game?; 2) What is the significance, if any, of technical noise trading for speculative price movements?; and 3) How can the phenomenon of a medium term expectational bias be explained? In what follows we offer a few speculative remarks on the first two issues[34].

The first problem, that of distinguishing the losers from the winners, involves dividing market agents into distinct groups. There are several studies that follow this approach (e.g., see Delong and others 1987 and Frankel and Froot 1987). But one of the problems here is that in distinguishing groups one implicitly (or explicitly) introduces some degree of irrationality into the system. The question of why the losers persist in their ignorance remains. Interestingly, however, the institutional characteristics of the various financial markets may help to shed light on this issue. In most financial markets it is reasonable to distinguish between two types of agents, those who continually buy and sell assets in order to profit from price changes in the very short-run (technical noise traders) and those who buy or sell for other reasons and who therefore trade relatively infrequently. In the case of the foreign exchange market, this delineation is quite straightforward. The first group of agents consists of professional currency dealers and the second of traders in goods and services and portfolio investors. These two types of agents base their decisions on different information sets that correspond to the specific business they are engaged in. A German exporter, for example, who happens to receive a dollar payment on June 15, 1984 (see Figure 3) will change it into deutschemarks without realizing that an appreciation run of the dollar was on its way (the same would be true for a Us investor who had decided to buy the stock of a specific German corporation)[35]. A technical currency trader, in contrast, having identified this run, would have bought dollars and held them as a «strategic position» until the rule indicated a switch. This occurred on August 10, 1984 and the trader would have sold the dollars bought earlier, possibly to another trader, but ultimately to some goods trader(s) or portfolio investor(s). The latter as a group have lost, although for any individual exporter (importer) or portfolio investor this loss represents only an opportunity loss rather than a realized cash loss, since those who sold dollars on June 15, 1984 and those who bought them on

August 10, 1984 are unlikely to be the same individuals.

In a similar manner, it is reasonable to suppose that the profit of noise traders in the stock market stem from the activities of all other market participants who try to make profits from holding the right shares (instead of buying and selling them at the right time)[36]. For many of the major players in the market (e.g., pension and mutual funds) membership in the latter group is unavoidable, since the portfolios these players hold must conform to their respective prospectuses by law. It is not possible for a tipical fund to be completely short or long in one particular asset and in many cases its prospectus explicitly precludes the type of short-term speculation outlined in this study. As a consequence, these players tend to be holders of stock rather then traders of stock. They base their decisions more on market fundamentals and thus disregard the very short (intraday) price runs. But, the losses that they incur because of trading at an unfavorable time (when viewed from the perspective of a few hours or days) are negligible when compared to the profits that they earn from holding the right shares in the medium-run. In effect, these fundamentals-oriented investors pay a small premium to the trade-oriented speculator. It is because the number of investors is so much greater than the number of speculators that the many small single losses of the former sum up to remarkable profits for the latter.

In terms of the second question, the analysis provided indirect evidence suggesting that technical noise trading served to exaggerate stock price movements during the October collapse. The theory of efficient markets however, assumes that the impact of noise trading on the overall movement of asset prices is insignificant. This belief rests on the argument that if noise traders do cause prices to move significantly away from their fundamental values, rational investors, who are armed with the true equilibrium model, will step in and trade against them, thereby driving prices back toward equilibrium. One of the key issues facing the literature is whether or not this is the case. Does noise trading actually serve to exaggerate price movements? If so, it must be the case that rational investors are failing to perform their function. But the question then becomes, why?

Delong and others (1987) and Frankel and Froot (1987) both construct models that distinguish noise traders as a separate group and both assume the existence of a group of agents who know the true equilibrium model. An extension to this approach would be to conjecture that no market agent is endowed with the true equilibrium model. As such, some agents may resort to noise trading while others may rely on fundamental analysis (or on some combination of these two basic approaches). But the investors who rely on fundamental analysis will be characterized by heterogeneous expectations. In such a world, then, investors will be less certain of the true value of a particular asset and will be, therefore, less likely to risk capital in order to speculate when prices deviate from expected values. As a consequence, the mechanism that glues prices to their equilibrium values (i.e., stabilizing speculation) becomes less than fully reliable, leading to the possibility that the actions of noise traders may tend to exaggerate price movements. The findings of this paper suggest that further research in this direction holds promise in the quest to understand behavior in financial markets.

Notes

[1] There are at least two reasons for this phenomenon. First, the growth in computer technology has facilitated greatly the use of technical trading models. (For a discussion on the use and availability of this technology see the November 1987 issue of Futures Magazine). Second, new financial instruments have been created, such as futures and options, which are particularly suitable for noise trading because they involve low margins, low transaction costs and high execution speed. The Group of Thirty Survey (1985) in the foreign exchange market reports a marked increase in the reliance on technical analysis. In response to the question, «Do you think the use of technical analysis has had a significant impact on the market?», 97% of the bank respondents and 87% of the securities houses replied in the affirmative.

[2] The existing literature on trading rule profits in the stock market, in the main, predates the 1970s, uses daily or lower frequency data and examines only one type of trading model, the filter rule (see Fama 1976). There has been some work examining the use and profitability of technical models in futures markets, but these studies do not examine stock index futures. See, for example, Neftci and Policano (1984) and Lukac, Brorsen and Irwin (1988). Both of these studies find technical analysis to be excessively profitable. In terms of the foreign exchange market, the existing literature on trading rule profits, for the most part, also examines only the filter rule. One exception here is Lukac, Brorsen and Irwin (1988),

which tests a number of technical trading systems in both the dollar-pound and dollar-deutschemark futures markets.

[3] The figures in the table are based on 5 day moving averages in order to filter out smaller fluctuations. If moving averages are not used, trends actually existing often can not be detected. A case in point are the studies that test for the existence of runs by comparing the sequence of the signs of daily exchange rate changes with that of a random series. In most cases these studies were unable to find significantly nonrandom sequences (e.g., see BURT, KAEN and BOOTH 1977, and DOOLEY and SHAFER 1983). But this result may well be due to the fact that only the original data were used. In this case oscillations around a significant trend cannot be distinguished from other, non-directional fluctuations. Since there are always some oscillations, a short-term moving average is also the most common tool in trading rooms to identify «underlying» runs.

[4] The importance of runs in the behavior of exchange rate and stock prices is also confirmed by the results of several random walk tests. It is shown in SCHULMEISTER (1987) and GOLDBERG and SCHULMEISTER (1988) that both price series deviated significantly from random walk behavior in the 1970s and 1980s. The most striking feature of the results is that the random walk hypothesis is more soundly rejected as the frequency of the data is increased (particularly if one moves from daily to hourly data in the case of stock prices). This phenomenon suggests that technical trading models will be able to exploit the existence of price runs more efficiently as the frequency of the data is increased.

[5] The calculation of returns assumes that there is always an open position of one dollar in the game (for any long position the equivalent of one dollar is borrowed in the DM market and invested in the dollar market and vice versa for a short position). The single rates of return from trading in the DM/$ market are therefore calculated as the difference between the selling price and the buying price of one dollar (expressed in Pfenning) and then converted into cents at the prevailing exchange rate. This absolute return in cents (r_j) is at the same time the relative rate of return. This calculation does not take into account transaction costs and the interest rate differential (neither bid and offer rates nor interest rates were available as daily series). However, it will be shown below that the size of both factors is negligible.

The total rate of return per year (R_i) is calculated as the annual sum of all single returns (r_j):

$$R_i = \frac{365}{D_i} \sum_{j=i}^{i} r_j$$

where D_i denotes the cumulative duration of all open positions in days.

[6] The first number appearing in each date in the figure, which ranges from 1 to 8, indicates the specific trading hour of the day, e.g., 7/2/4 signifies 7th hour of trading (3:00 p.m.) on the 2nd of April.

[7] The single rates of return are calculated as the difference between the selling price and the buying prices, divided by the price at which the stocks were initially bought or sold. The rate of return is calculated in the same way as in the case of the foreign exchange market. When using hourly data, D_i is calculated as the number of cumulative trading hours divided by the (standardised) number of trading hours per day.

[8] The typical description of this phenomenon in trader jargon is «cut losses short and let profits run», or «it is better to be right at the right time than to be simply right».

[9] In a strict methodological sense t-statistics cannot be used if the sample distribution is significantly leptokurtotic. In econometric practice, however, this restriction is seldom taken into account. For the purpose of this study the use of t-statistics seems less problematic since the distribution of the single rates of return is skewed to the right. This implies that the number of relatively large losses is actually smaller than in the normal case.

[10] The daily trading model examined in Table 2, which generated an unusually low t-statistic, was chosen because the graphical presentation of a model with only one moving average is much less cluttered than that whith two moving averages (Figure 3). In the foreign exchange market the moving average models with one moving average generally performed much worse than those operating with two moving averages. This fact is demonstrated below.

[11] The hourly data include only the second and third quarters of the middle years of the six sub-periods examined (1971, 1974, 1977, 1980, 1983 and 1986). The decision to limit the size of the hourly data set was predicated on the fact that each observation had to be individually loaded onto the computer (i.e., the data could not be found on computer tape or disc).

[12] For example, in the case of a moving average model, the two moving averages cross most often within the day (the optimal transaction price), but with daily data the price signal is received only at the end of the day. If prices move too quickly, so that the actual transaction price differs substantially from the optimal transaction price, the particular transaction in question will often produce a lower profit, possibly even a loss.

[13] This pattern was elaborated upon in a quantitative manner only for the DM/$ exchange rate (Table 1). However, the fact that the profitability of the trading rules in the stock market is so similar to that in the foreign exchange market suggests that the underlying price pattern in the short run is also qualitatively the same in both markets, i.e., they both consist of a sequence of many small fluctuations and relatively few but persistent runs. In addition, medium-term trends of rising or falling stock prices also seem to be due primarily to the fact that during such periods the price runs that move with the trend last substantially longer on average than the counter-movements. This can be concluded from the fact that the long positions signalled by the trading rules lasted longer on average than the short positions during the bull market of 1982-1987, whereas the opposite was the case during the bear market of 1973-1974.

[14] The specific pattern of stock prices also explains why the «fastest» daily models were at the same time also the most profitable of the daily models. The Dow rule (when based on daily data) performed much worse in the stock market than the other trading systems presented in Table 8 because the rule often neglects short but still persistent price runs, i.e., runs which do not lead the price beyond the most recent high or low.

[15] The official quotation of bid and offer rates for the DM/$ trade usually shows a spread of 0.001 DM, so that 0.04 percent is an upper limit for the relative spread (based on a DM/$ rate of 2.5). This translates into estimated costs per transaction of 0.02 percent. LEVICH (1979) arrives at a slightly higher estimate for the 1970s (0.025 percent). Since then transaction costs have diminished, mainly because of leverage effects. The presumption that 0.02 percent represents an

upper limit is confirmed by bankers who indicated in interviews that the actual spread is much lower than the official quotations for most interbank transactions (SWEENEY 1986, estimates transaction costs at 0.0125 percent).

[16] Note that the use of these trading rules implies that the speculator is always in the game. Consequently, every buy and sell signal requires two transactions, one to close the existing open position and another to open a new position of the opposite sign. The number of trades, therefore, is always twice the number of open positions.

[17] These costs arise because any long position in dollars involves collecting dollar interest rate payments and incurring deutschemark interest rate expenses; vice versa for a dollar short position.

[18] The issue of transaction costs for technical stock market trading is discussed in more detail in GOLDBERG and SCHULMEISTER (1988).

[19] The difference between the rate at which dividends are paid and the prevailing interest rate does not affect the profitability of technical stock trading, at least when the trading is based on hourly data (the average duration of long and short positions was practically the some in each of the 6 sample periods).

[20] This figure is based on average total costs of 39.6 percent annually (396 trades per year multiplied by the sum of 0.025 percent in commissions and 0.075 percent in slippage costs), an average gross return of 51.2 percent (Table 6) and a margin of 20 percent. Although regulations permit market agents to only borrow up to 50 percent of the capital invested, many of the major market players are able to obtain exemptions from this rule.

[21] Although the analysis here does not examine the profitability of the trading rules with S&P 500 futures prices, it is assumed that the size and pattern of returns produced with such data will at least approximate the returns obtained with cash prices. There are two reasons for this assumption. First, the futures price rarely deviates from the corresponding cash price by more than 2 percent at any one time due to index arbitraging (SEC 1987). Second, it is generally recognized that price volatility (and therefore the number of persistent runs) is greater in the futures market.

[22] STOLL and WHALEY (1987), report that the average dollar value of trading in the S&P 500 contract alone — $12 billion worth of equity value each day — is substantially greater than that in the spot market. As a result of this liquidity, traders are able to execute trades with a much smaller market impact (and thus with substantially lower slippage costs) than if the trades are executed in the separate stocks (SEC 1987). In addition, traders do not have to wait for non-negative price changes before going short as is the case in the NYSE.

[23] Portfolio insurance involves the use of hedging strategies in order to protect portfolios against unfavorable price movements. These strategies usually use futures contracts to continuously rebalance positions between stock and cash (Treasury bills), thereby assuring the maintenance of some minimum portfolio value (this is referred to as dynamic hedging). The term «program trading», on the other hand, is often used to refer to the activity of index arbitraging. Index arbitragers attempt to exploit the spread between the cash and futures prices whenever this spread deviates from its arbitrage equilibrium value (see SANTONI 1987, for a description of both activities).

[24] During 1983 and 1986 (2nd and 3rd quarters) the average duration of all open positions generated by the moving average model (MA:8 hours) was 1.3 days. For the momentum model (K = 7 hours) and the Dow rule the average duration during the same period was 1.4 and 1.8 days respectively.

[25] The Katzenbach study was prepared by NICHOLAS B. KATZENBACH at the request of the NYSE. This conclusion, that the markets for stock-index futures are more short-term and speculative in nature, is also confirmed by the *Report of the Presidential Task Force on Market Mechanisms* (1988), commonly referred to as the Brady Report.

[26] For a review of the events during the earlier episode see SEC (1987) and for the more recent episode sea *The Presidential Task Force on Market Mechanisms* (1988).

[27] The basic scenario underlying this point of view begins with a decline in the price of index futures to a level which is substantially below the arbitrage equilibrium value. This triggers short side index arbitrage and the unwinding of previously established long arbitrage positions. Both of these actions involve the selling of stocks and the buying of futures and cause cash prices to decline. This in turn compels the portfolio insurers to begin selling futures in an attempt to minimize downside risk, thereby depressing futures prices and creating once more a significant disparity between the spot and futures prices. The cycle repeats itself when the index arbitragers step in again.

[28] The hourly Dow Jones price series is used in lieu of the hourly S&P 500 price series because the Dow Jones data were more easily obtained at the time of the analysis. Note, however, that the profitability of the technical rules is rather similar for both price series (see Table 6).

[29] The study by LUKAC, BRORSEN and IRWIN (1988A), has found that many of the technical trading systems examined are on the same side of the market more than 70 percent of the time.

[30] Another piece of news that also played a role on Wednesday was the annoucement that members of Congress were filing legislation to eliminate the tax benefits associated with the financing of corporate takeovers (see the Brady Report).

[31] Figure 6 was taken directly from *The Presidential Task Force...* 1988. The vertical lines were added to the figure to indicate when the spread between the S&P 500 index and the respective price of a futures contract reached its extreme highs and lows. The precise location of these minima and maxima of the spread can be found in Figure 15 of *The Presidential Task Force...* 1989.

[32] This conclusion is consistent with a growing body of evidence which suggests that price movements in the futures markets, as a rule, either precede (or are larger initially) than those in the spot market, the former being transmitted to the latter via index arbitraging. See, for example, FINNERTY and HUN (1987), SEC (1987), STOLL and WHALEY (1987), KAWALLER, KOCK and KOCK (1987), *The Presidential Task Force...* (1988), and the numerous newspaper and magazine articles documenting the events surrounding October 19th. The SEC (1987) study also finds that the futures market led the spot market during the record drop (at that time) of September 11 and 12, 1986.

[33] Note that the term «program trading strategies» refers to other types of insurance and arbitrage strategies and not to noise trading.

[34] The possible relevance of a medium-term expectational bias in the foreign exchange market is investigated in SCHULMEISTER (1987). This study hypothesises that a medium-term expectational bias in the foreign exchange market can be explained by the interaction of disequilibria in both the goods market and in the asset market.

[35] Note that a number of the large international nonfinancial corporations treat their foreign exchange activities as discrete profit centers, devoting substantial sums of money for speculative activities (see the GROUP OF THIRTY SURVEY 1985).

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