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Abstract

This study analyzes the interaction between the aggregate trading behavior of technical models and stock price fluctuations in the S&P 500 futures market. It examines 2580 widely used trading systems based on 30-minutes-prices. The sample comprises trend-following as well as contrarian models. I show that technical trading exerts an excess demand pressure on the stock market. This is because technical models produce clusters of trading signals that are on the same side of the market, either buying or selling. Initial stock price changes triggered by news are strengthened by a sequence of trading signals produced by trend-following models. Once 90% of the models have signaled a particular position, stock prices tend to move in the direction congruent with the position-holding of the models. This phenomenon has to be attributed to the transactions of non-technical traders, perhaps amateurs. Once price movements lose their momentum, contrarian technical models contribute to reversals of the trend.

Keywords: Technical trading, stock price dynamics, momentum effect, reversal effect

JEL classification: G12, G13, G14

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The Interaction between the Aggregate Behavior of Technical Trading Systems and Stock Price Dynamics*

1. Introduction: Stock price dynamics, market efficiency and technical analysis

The debate over the the predictability of stock returns and the exploitability of the implied pattern in stock price dynamics, has intensified over the past 15 years (for an overview see Campbell, 2000; Cochrane, 1999; Lo-MacKinlay, 1999; Shiller, 1999). Particular attention has been paid to the "momentum effect" and the "reversal effect".

The first effect refers to the phenomenon that stock prices often move in trends which can be profitably exploited following "momentum strategies" (Fama-French, 1989; Jegadeesh-Titman, 1993; Chan-Jegadeesh-Lakonishok, 1996; Goetzmann-Massa, 2000). The second effect refers to reversals in stock price trends which can be profitably exploited following "contrarian strategies" (DeBondt-Thaler, 1985, 1987; Chan, 1988; Fama-French, 1989; Jegadeesh, 1990; Lo-MacKinlay, 1990; Lehman, 1990; Jegadeesh-Titman, 1995).

The literature has investigated many reasons why asset prices move in a sequence of trends, e. g., psychological "biases" like overconfidence (Daniel-Hirshleifer-Subrahmanyam, 1998; Daniel-Titman, 2000), overreaction to news (DeBondt-Thaler, 1985, 1987; Lakonishok-Shleifer-Vishny, 1994), changes in "expectational regimes" (Barberis-Shleifer-Vishny, 1998), loss aversion as in prospect theory (Barberis-Huang-Santos, 2000), the role of emotions and market moods (Coval-Shumway, 1998; Hirshleifer-Shumway, 2003), the related herding behavior (Scharfenstein-Stein, 2000; Froot-Scharfstein-Stein, 1992; Teh-DeBondt, 1997; Ottaviani-Sorensen, 2000, Hirshleifer-Teoh, 2003), and imperfect knowledge (Frydman-Goldberg, 2007).

The momentum and contrarian strategies as developed in the literature represent hypothetical constructions which are not used in practice. However, there exist a great variety of trading techniques used in practice which aim to exploit asset price trends and their reversals, i. e., the trend-following and contrarian models of technical analysis.

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Technical analysis is the most widely used trading technique in financial markets.[1]) Despite its popularity, technical analysis has not been analyzed empirically as a possibly important reason for the "trending" of stock prices. Somewhat surprisingly, technical trading has also been widely neglected in the behavioral finance literature. Neither textbooks like Shleifer (2000) nor monographs on the stock market like Shiller (2000) deal with the role of technical analysis. The same is true for survey articles on behavioral economics like DeBondt-Thaler (1996), Mullainathan-Thaler (2000), Shiller (1999), Hirshleifer (2003) or Barberis-Thaler (2003).

When theoretical models take "noise" trading into consideration assumptions are made which miss the essence of technical analysis (De Long-Shleifer-Summers-Waldmann, 1990A and 1990B; Frankel-Froot, 1990; Cutler-Poterba-Summers, 1991; Hong-Stein, 1999; Daniel-Titman, 2000). First, these models assume that feed-back traders just follow the most recent price movement, e. g., they buy whenever the price is rising. However, in practice any technical model produces only one signal per trend. Second, these models neglect the fact that technical traders use not only trend-following strategies but also contrarian strategies.

Studies on technical analysis have so far focused on its possible profitability. Many of these studies report "abnormal" returns in the stock market as well as in the foreign exchange market.[2]) In a recent paper, I re-examine the profitability of technical stock trading using not only daily but also intraday data (Schulmeister, 2007B). I find that the profitability of 2580 technical models based on daily prices has become unprofitable over the 1990s. However, these models would have remained profitable when based on 30-minutes-data.

The present paper complements the profitability study. It analyzes the causality running from the aggregate trading behavior of the same 2580 technical models in the S&P 500 futures market based on 30-minutes-data to stock price dynamics.

Motivation for this investigation comes from several places. First, the aggregate trading behavior of technical models in the stock market has not yet been explored (for the foreign exchange market, see Schulmeister, 2006, 2007D). Second, an analysis of the impact of aggregate trading signals on subsequent stock price movements will help to better understand the omnipresence of technical analysis on the screens in trading rooms (even

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[1]) The use of technical analysis in the foreign exchange markets is documented by Taylor-Allen, 1992; Cheung-Wong, 2000; Cheung-Chinn, 2001; Cheung-Chinn-Marsh, 2004; Gehrig-Menkhoff; 2004, 2005 and 2006; Menkhoff-Taylor, 2007. Irwin-Holt, 2004, provide evidence about the popularity of technical analysis in futures markets.

[2]) For stock market studies see Goldberg-Schulmeister (1988), Brock-Lakonishok-LeBaron (1992), Hudson-Dempsey-Keasey (1996), Sullivan-Timmerman-White (1999), Gunasekarage-Power (2001), Fernandez-Rodriguez-Gonzales-Martel-Sosvilla-Rivero (2000, 2005), Kwon-Kish (2002), Wong-Manzur-Chew (2003), Jasic-Wood (2004) and Chang-Metghalchi-Chan (2006). "Abnormal" returns of technical analysis in foreign exchange markets are reported by Schulmeister (1988, 2007A, 2007C), Levich-Thomas (1993), Menkhoff-Schlumberger (1995), Gencay-Stengos (1998), Chang-Osler (1999), Neely-Weller (1999), Gencay (1999), LeBaron (1999), Osler (2000), Maillet-Michel (2000), Neely-Weller (2003), Okunev-White (2003), Ohlson (2004), Neely-Weller (2006). Excellent surveys of studies on technical analysis are Park-Irwin (2004) for futures markets in general, and Menkhoff-Taylor (2007) for foreign exchange markets in particular.

non-technical monitor the most popular models to tackle Keynes' "beauty contest" problem (for a recent treatment of this problem see Allen-Morris-Shin, 2006). Third, such an analysis might provide some empirical underpinning for agent-based models which analyze the interaction between heterogeneous actors in asset markets.[3])

The main results of the present study are as follows:

- When technical 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. Hence, the aggregate trading behavior of technical models exerts an excess demand pressure on the stock market.
- A strong feed-back mechanism operates between stock price movements and the transactions of technical models. Rising (falling) stock prices cause increasingly more technical models to produce buy (sell) signals, which in turn strengthen the upward (downward) trend.
- After a certain portion of technical models has reversed their open positions, stock prices continue to move in the direction congruent with the initial position.

2. The technical trading systems investigated

In this section I sketch shortly how moving average models, momentum models and RSI models work and which types of trading signal generation are used.[4]) To simplify the presentation it is assumed that the models are applied to daily data.

Moving average models consist of a short-term moving average (MAS_j) and a long-term moving average (MAL_k) of past prices. The length j of MAS usually varies between 1 day (the original price series) and 10 days, the length k of MAL usually lies between 10 and 30 days.

The basic trading rule of average models is as follows (signal generation 1):

Buy (go long) when the short-term (faster) moving average crosses the long-term (slower) moving average from below and sell (go short) when the converse occurs. Or equivalently: Open a long position when the difference (MAS_j-MAL_k) becomes positive, otherwise open a

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[3]) LeBaron (2006) and Hommes (2006) provide excellent surveys of these models. 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 (2007) analyze expectations formations and transaction behavior of bulls and bears in currency markets under imperfect knowledge.

[4]) For an introduction into technical analysis see Neely (1997). Kaufman (1987) provides an excellent treatment of the different methods of technical analysis; other textbooks are Murphy (1986), Pring (1991) and Achelis (2001). The increasingly popular technical "day trading" is dealt with in Deel (2000) and Velez-Capra (2000).

short position. If one expresses this difference as percentage of MAL_k one gets the moving average oscillator:

$MAO(j,k)_t = [(MAS_{j,t}-MAL_{k,t})/MAL_{k,t}]*100$

The second type of model works with the relative difference (rate of change in %) between the current price and that i days ago:

$M(i)_t = [(P_t - P_{t-i})/ P_{t-i}]*100$

The basic trading rule of momentum models is as follows (signal generation 1):

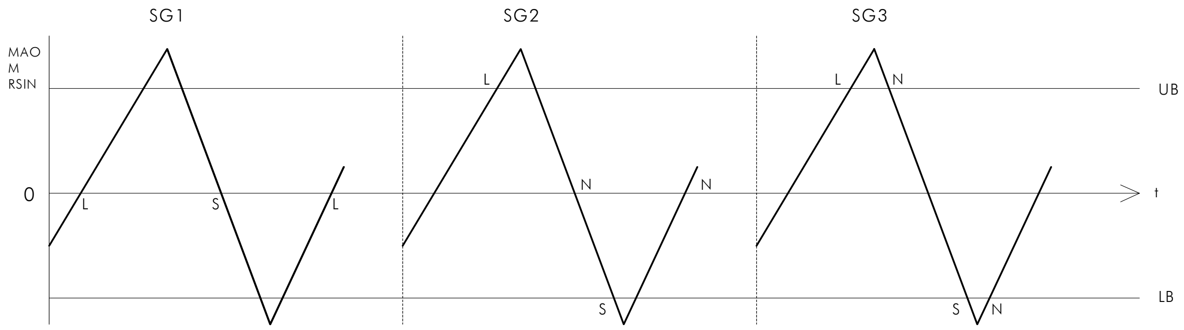
Buy (go long) when the momentum M(i) turns from negative into positive and sell (go short) in the opposite case.

The variables MAO(j,k) or M(i) are called "oscillators" because they fluctuate around zero.

The basic trading rule (SG 1) of moving average models and momentum models is trend-following since $MAS_{j,t}$ (P_t) exceeds (falls below) $MAL_{k,t}$ (P_{t-i}) only if an upward (downward) price movement has persisted for some days.

The modifications of the basic version of moving average and momentum models use a band with varying width around zero combined with different rules of opening a long, short or neutral position. These rules (SG 2 to SG 6) are either trend-following or contrarian.

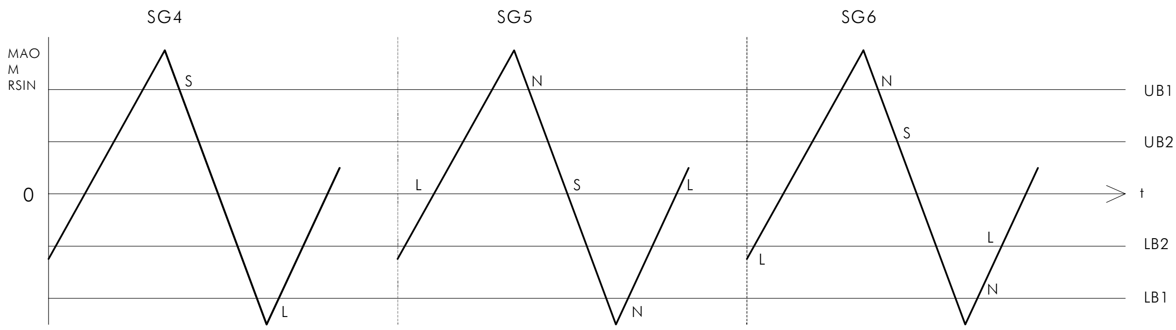
According to signal generation 2 one opens a long (short) position whenever the oscillator crosses the upper (lower) bound from below (above). When the model holds a long (short) position and the oscillator crosses the zero line from above (below) then the model switches to a neutral position. A simple graph may clarify the meaning of this rule by comparing it to SG 1:



Rule SG 2 is "more" trend-following than SG 1 since it opens a long or short position at a later stage of a price trend. At the same time SG 2 is more "cautious" than SG 1 since it always holds a neutral position between switching from long to short and vice versa.

Rule SG 3 differs from SG 2 insofar as the former switches from an open to a neutral position earlier. Whenever the oscillator crosses the upper (lower) band from above (below) rule SG 3 turns from long (short) to neutral. A momentum oscillator, e. g., closes a long position even if the current price still exceeds the price i days ago, provided that the (positive) rate of change $[(P_t - P_{t-i})/ P_{t-i}]*100$ is declining and falls below the level of the upper bound.

The trading rules SG 4 to 6 are contrarian, i. e., they try to identify "overbought" ("oversold") situations. An overbought situation is indicated when the moving average (momentum) oscillator (though still positive) is falling below the upper bound of the band. If the oscillator is rising and penetrates the lower bound from below the situation is considered oversold. A simple graph shows the differences between the 3 contrarian trading rules:



Rule SG 4 is always either long or short. A trader switches from a long (short) to a short (long) position once the oscillator crosses the upper (lower) bound from above (below). Hence, even if the rate of price change in the case of a momentum model is still positive SG 4 switches to a short position once this rate falls below the upper bound.

Rule SG 5 is more "cautious" than SG 4 insofar as the former goes at first neutral when the oscillator penetrates the upper (lower) bound from above (below), and switches to a short (long) position only if the oscillator penetrates the zero line.

Rule SG 6 operates with a second (inner) band marked by UB2 and LB2 (UB1>UB2>LB2>LB1). This model holds a neutral position whenever a falling (rising) oscillator lies between UB1 and UB2 (LB1 and LB2) and, hence, is less often neutral as compared to SG 5. Rule SG 6 can be considered a combination of SG 4 and SG 5. At the extreme values of UB2 (LB2) the model SG 6 is identical either with SG 4 (when UB2=UB1 and LB2=LB1) or with SG 5 (when UB2=LB2=0).

One of the most popular indicators for identifying overbought and oversold conditions is the so-called Relative Strength Index (RSI). Since the strategy of following this index is contrarian only the trading rules SG 4 to SG 5 can be applied. The n-day RSI is defined as follows (Kaufman, 1987, p. 99):

$RSI(n)_t = 100 – \{100/[1+Up_t(n)/Down_t(n)]\}$

Where

D_i is the (daily) price change:

$D_i = P_{t-i+1} - P_{t-i}$ for i = 1…….n

And

$Up_t(n)$, $Down_t(n)$ are the average positive or negative price changes within the n-day interval.

$Up_t(n) = \Sigma D_i/n$ for $D_i>0$

$Down_t(n) = \Sigma D_i/n$ for $D_i<0$

The size of the RSI(n) oscillator does not only depend on the overall price change $P_t - P_{t-n}$ (as the momentum oscillator) but also on the degree of monotonicity of this change, e. g., the less countermovements occur during an upward (downward) trend the higher (lower) is RSI(n) for any given price change $P_t - P_{t-n}$. If the RSI(n) falls (rises) again below (above) a certain level (the upper/lower bound of the RSI oscillator) the situation is considered overbought (oversold).

The original RSI fluctuates between 0 and 100. To make this oscillator comparable to the moving average and the momentum oscillator, respectively, one can calculate a normalized RSI (=RSIN) which fluctuates around zero:

$RSIN(n)_t = (1/100)*[RSI(n)_t - 50]*2$

The contrarian trading rules SG 4, SG 5 and SG 6 can then be applied to this normalized index in the same way as to the moving average oscillator and the momentum oscillator, respectively.

The study investigates a great variety of technical models. In the case of moving average models all combinations of a short-term moving average (MAS) between 1 and 12 days and a long-term moving average (MAL) between 6 and 40 days are tested under the restriction that the lengths of MAL and MAS differ by at least 5 days. Hence, 354 moving average models are tested for each of the six types of signal generation, in total 2.124 models. In the case of momentum models and RSIN models the time span runs from 3 to 40 days (38 models per type of signal generation). 5)

3. The performance of technical trading systems in the S&P 500 futures market based on 30-minutes data

In this section I summarize shortly the main results of the complementary study on the profitability of 2580 technical models in the S&P 500 futures market based on 30-minutes-data between 1983 and 2000.

5) The selection of the models, the calculation of their profitability, the role of transaction costs, the switching of futures contract, the margin requirements and the estimation of the measure of riskiness of technical trading are documented more in detail in Schulmeister (2007A).

All models would have produced an average gross return of 8.8% per year between 1983 and 2000 (figure 1). Due to the high number of transactions the net rate of return is only 4.3% per year (figure 1). Since the best performing models are trading more often than all models, the distribution by the net rate of return is less skewed to the right than the distribution by gross returns (figures 1 and 2).

Figure 1: Distribution of 2580 trading systems by the gross rate of return per year 1983-2000
S&P 500 futures market, 30 minutes data

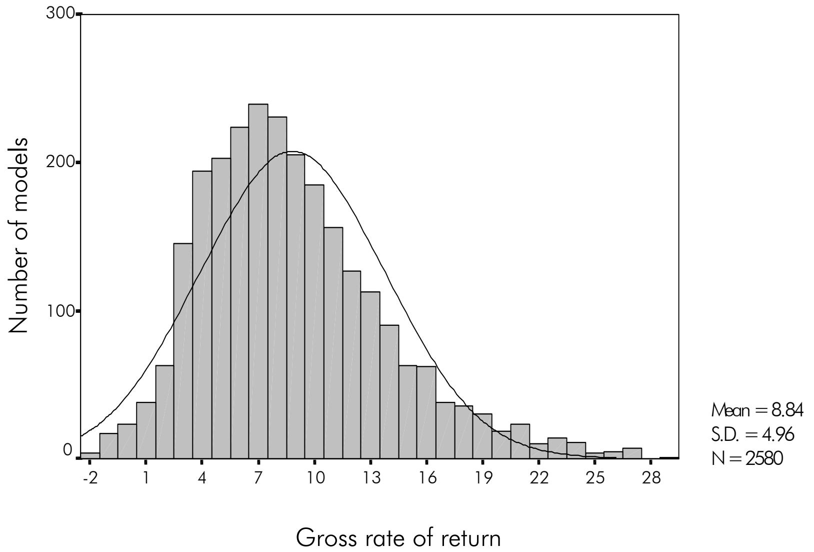
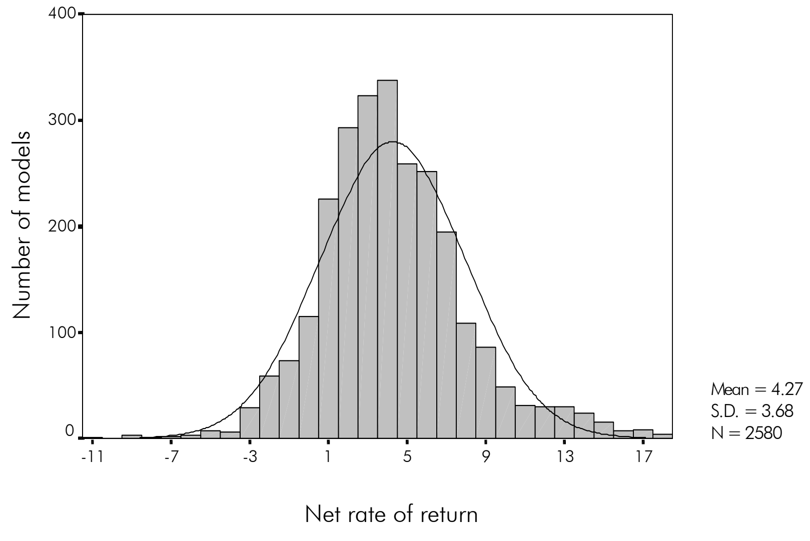
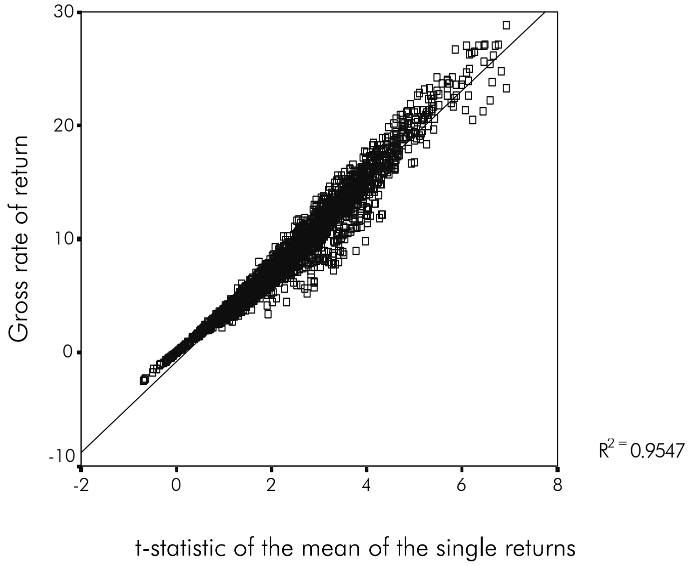


Figure 2: Distribution of 2580 trading systems by the net rate of return per year 1983-2000
S&P 500 futures market, 30 minutes data



The t-statistic of the mean of the single rates of return exceeds 2.0 in most cases (figure 3), it amounts on average over all models to 2.4 (table 1). These results indicate that there was rather little risk associated with technical stock trading based on 30-minutes-data if traders had rigidly adhered to a particular model out of the sample of 2580 models.

Figure 3: Profitability and riskiness of 2580 technical trading systems 1983-2000
S&P 500 futures market, 30 minutes data



When trading S&P 500 futures based on 30-minutes-data the RSIN models and the momentum models (GRR: 11.5% and 10.1%, respectively) perform better than the moving average models (GRR: 8.4% - table 1). The contrarian rules SG 4 to SG 6 are significantly more profitable than the trend-following rules SG 1 to SG 3 (GRR: 10.9% and 6.4%, respectively).

Over the entire period between 1983 and 2000 almost all of the 2580 technical models are profitable, 98.7% of them produce a positive gross rate of return (table 3).

As regards the pattern of profitability the following observations can be made (table 1). First, the number of profitable positions is always smaller than the number of unprofitable positions. Second, the average return per day during profitable positions is lower than the average return (loss) during unprofitable positions (the average slope of price movements during the - relatively longer lasting - profitable positions is flatter than during the short lasting unprofitable positions). Third, the average duration of profitable positions is several times greater than that 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").

Table 1: Components of the profitability of technical trading systems
S & P 500 futures market, 30-minutes-data, 1983-2000

	Share of profitable models	Gross rate of return per year	Net rate of return per year	t-statistic	Mean for each class of models: Profitable positions: Number per year	Return per day	Duration in days	Unprofitable positions: Number per year	Return per day	Duration in days
By type of model										
Moving average models	98.5	8.4	4.5	2.34	74.7	0.39	2.8	118.0	– 0.57	1.1
Momentum models	100.0	10.1	2.3	2.61	147.5	0.42	1.8	235.9	– 0.69	0.5
Relative strength models	99.6	11.5	4.0	3.08	148.3	0.50	1.7	225.7	– 0.66	0.7
By type of signal generation										
SG 1	95.4	7.3	2.6	1.86	80.5	0.32	3.4	152.9	– 0.50	1.1
SG 2	96.4	4.7	2.1	1.35	46.9	0.34	3.7	76.2	– 0.51	1.4
SG 3	100.0	7.3	3.9	2.37	65.3	0.47	2.0	104.6	– 0.73	0.7
SG 4	99.8	12.0	6.5	3.02	111.3	0.39	2.6	156.5	– 0.54	1.2
SG 5	100.0	9.8	4.5	2.83	102.2	0.44	1.9	160.4	– 0.66	0.7
SG 6	100.0	10.8	5.3	2.88	108.0	0.42	2.2	163.8	– 0.58	1.0
Total	98.7	8.8	4.3	2.43	87.6	0.40	2.6	137.9	– 0.59	1.0

The t-statistic tests the mean of the single returns against a hypothesized value of zero.

4. Price effects of the aggregate trading behavior of technical models in the stock futures market

This section investigates the impact of the use of different trading models on stock price dynamics. In a first step an index of the aggregate transactions and open positions of the 2580 technical models is calculated for any point in time. Then the relationship between the level and the change of the net position index, and stock price movements is analyzed.

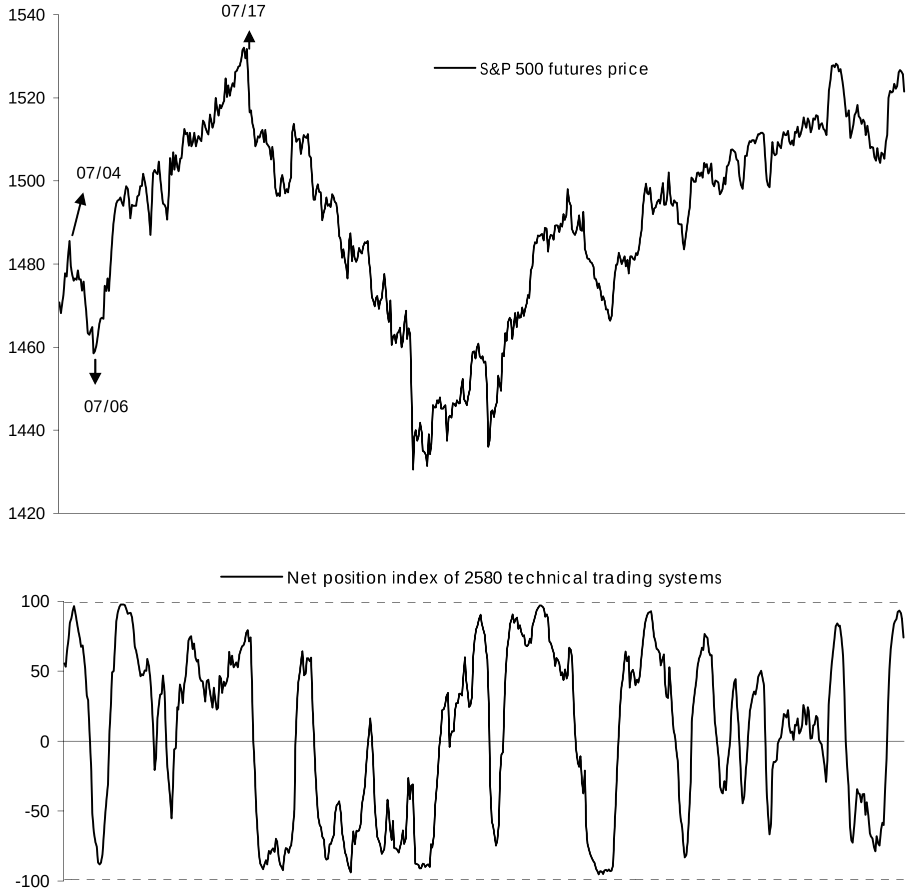
4.1 The aggregation of trading signals

The open positions of the 2580 trading models are aggregated in the following way. The number +1 (-1) is assigned to any long (short) position of each single model (to any neutral position the number 0 is assigned). The net position index (PI) is then calculated for every 30-minutes-interval as the sum of these numbers over all models divided by the number of models (2580). Hence, an index value of +100 (-100) means that 100% of the models hold a long (short) position. A value of 90 (-90) indicates that 95% of the models are long (short) and 5% short (long). The percentage share of models holding a long position can generally be derived as [PI+100]/2.

The net transaction index (TI) is simply the first difference of the net position index. Its theoretical maximum (minimum) value is twice as high (in absolute terms) as in the case of the net position index since the number of transactions is always twice the number of open positions. The extreme value of +200 (-200) would be realized if all models change open position from short to long (from long to short) between two consecutive trading intervals (implying 5160 buy transactions or sell transactions, respectively).

In order to investigate the extent to which the signals from technical models balance each other, the components of the net transaction index are also documented, i.e., the number of buys and sells during each 30-minute-interval (divided by the number of all models).

Figure 4: Aggregate trading signals and stock price dynamics
July and August 2000, 30-minutes-data



4.2 Similarities in position taking of technical models

Figure 4 shows the gradual adjustment of the 2580 technical models to stock price movements, using S&P 500 futures trading during July and August 2000 as example. Due to a steep downward run between July 4, and July 6, almost all models change their positions from long to short. The strong - though frequently interrupted - upward price trend between

July 6, and 17, causes roughly 75% of the models to hold long positions most of the time (PI mostly exceeds 50). The opposite is true during the downward movement of stock futures prices over the second half of July. The fall of prices is so strong that roughly 90% of all models hold short position over this period (PI lies mostly below 80).

A careful observation of the relationship between stock price movements and the aggregate open position of the 2580 trading systems reveals the following:

- Most of the time the majority of the models are on the same side of the market, either long or short (PI oscillates almost never around zero – this would be the case if stock prices followed a random walk).
- The process of changing open positions in response to a new price trend usually takes off 1 to 3 trading intervals after a local price minimum (maximum) has been reached. If the trend continues it takes between 10 and 20 trading intervals (1 and 2 days) to gradually turn the positions of (almost) all models from short to long or vice versa.
- After all technical models have adjusted their open positions to the current trend, the trend often continues for some time.

Table 2 quantifies some of these observations. On 18.3% of all 30-minutes-intervals of the entire sample period more than 85% of the models hold a long position (PI>70), and on 16.1% of all intervals more than 85% of the models hold a short position (PI<-70). Hence, on 34.4% of all trading intervals more than 85% of the models hold the same – long or short – position. On 53.5% of the sample period more than 75% of the models hold the same open position (|PI|>50).

By contrast, on only 9.4% of all 30-minutes-intervals are short and long positions roughly in balance (|PI|<10). These situations occur primarily during the change of the models from short to long positions and vice versa. In these phases the share of neutral positions reaches a maximum (33.8% of the models hold neutral positions when |PI|<10).

On 66.4% of all 30-minutes-intervals less than 5% of the models execute buy or sell signals (|TI|<10). There are two reasons for that. First, the majority of the models hold the same – long or short – position for most of the time (little trading occurs during these periods, it concerns mainly "fast" models reacting to short-term stock price movements against the underlying trend). Second, the process of changing open positions evolves only gradually. If this process is relatively slow then only 5% of the models or even less change their position on average. If this process is relatively fast then between 5% and 15% of the models change their position per trading interval: the transaction index lies between 10 and 30 (between -10 and -30) on 15.6% (15.1%) of all 30-minutes-intervals. Only on roughly 3% of all intervals is technical trading more intense in the sense that more than 15% of the models execute signals within 30 minutes.

Table 2: Distribution of time by positions and transactions of 2,580 technical trading systems
S & P 500 futures trading based on 30-minutes-data

Net position index	Aggregate positions				
	Share in total Sample period in %	Mean of the net position index	Distribution by type of position		
			Long	Short	Neutral
> 70	18.29	85.22	88.86	– 3.64	7.51
50 - 70	9.97	60.15	70.63	– 10.48	18.89
30 - 50	9.62	40.06	56.84	– 16.78	26.37
10 - 30	9.46	19.98	44.27	– 24.30	31.43
–10 - 10	9.36	0.08	33.12	– 33.04	33.84
–30 - –10	8.94	– 19.96	24.03	– 43.98	31.99
–50 - –30	9.17	– 40.05	16.18	– 56.23	27.59
–70 - –50	9.05	– 60.09	9.75	– 69.84	20.41
< –70	16.14	– 85.43	3.46	– 88.88	7.66
Total	100.00	2.66	41.12	– 38.47	20.41

	Aggregate transactions			
	Share in total Sample period in %	Mean of the net transaction index	Distribution by type of transaction	
			Buy	Sell
> 70	0.01	81.38	81.38	0.00
50 - 70	0.09	56.33	56.47	– 0.14
30 - 50	1.30	35.84	36.18	– 0.34
10 - 30	15.55	16.49	17.61	– 1.12
–10 - 10	66.35	0.03	4.56	– 4.52
–30 - –10	15.14	– 16.56	1.13	– 17.69
–50 - –30	1.41	– 36.24	0.30	– 36.54
–70 - –50	0.13	– 57.76	0.12	– 57.88
< –70	0.02	– 76.37	0.00	– 76.37
Total	100.00	– 0.00	6.46	– 6.46

Table 2 shows also that technical models 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 15 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 roughly 4.6 which implies that only 2.3% 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 unstable models is more similar as compared to stable models.[6]) E. g.,

[6]) Stable models are profitable over each of 6 subperiods between 1983 and 2000, all other models are classified as unstable (see Schulmeister, 2007B for the performance of the 2580 models according to this criterion).

more than 80% of the models hold the same - long or short - position on 53.2% of all days in the case of unstable models but on only 42.7% in the case of stable models. Position holding of trend-following models is more similar as compared to contrarian models. E. g., more than 80% of contrarian models hold the same open position on 43.5% of all trading intervals, however, in the case of trend-following models this is true on 55.5% of all intervals.

Table 3: Similarity of different types of technical trading systems in holding open positions
S & P 500 futures trading based on 30-minutes-data

	Relative share of models holding the same – long or short – position		
	More than 90% (|PI| > 80)	More than 80% (|PI| > 60)	More than 70% (|PI| > 40)
		Share in total sample period in %	
Types of models			
By stability			
Stable	23.41	42.66	61.56
Unstable	32.19	53.20	70.45
By type of trading strategy			
Trend-following	35.66	55.51	71.97
Contrarian	21.81	43.50	63.74
All models	23.59	44.11	62.96

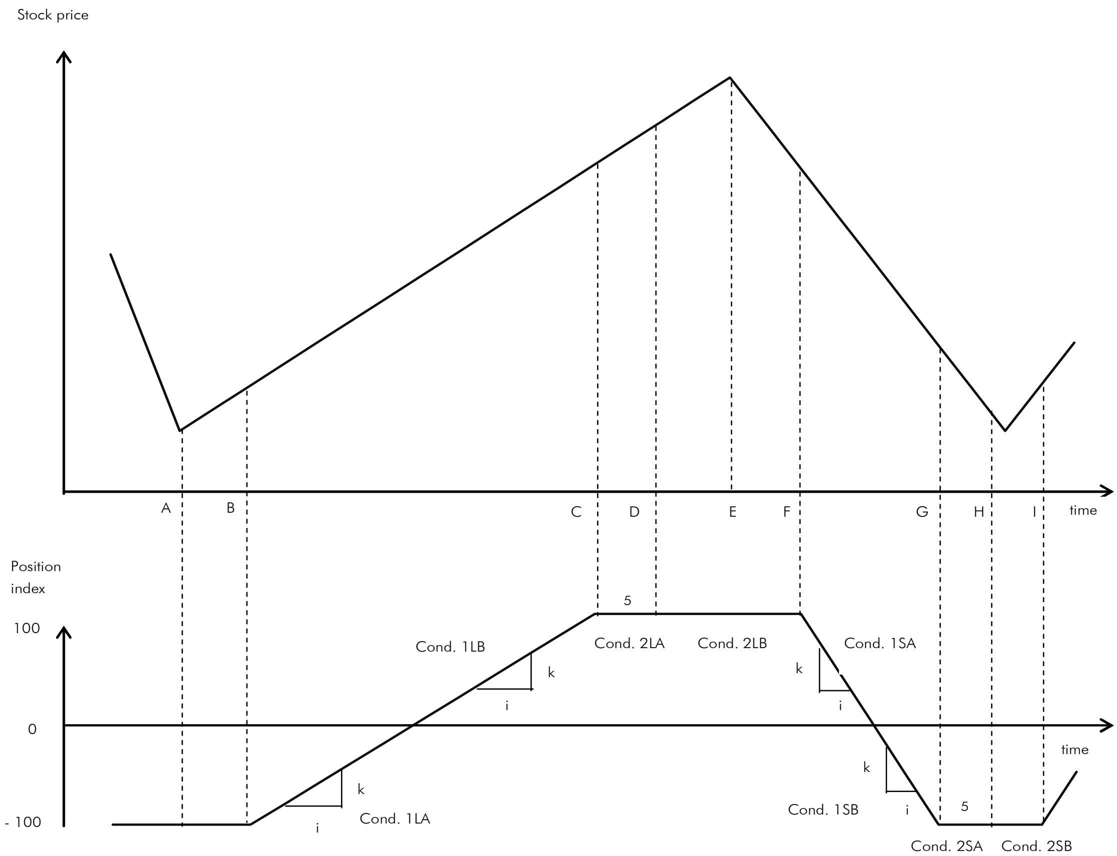
The pattern in the signal generation of technical models implies that their users trade as if they were "herding" or "cascading" (Hirshleifer-Teoh, 2003, provide an excellent review of the respective literature). However, since every "technician" conceives a signal of his preferred model as private information, 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. Hence, the aggregate behavior of technical models has to be considered as clustering and not as herding or cascading (according to the taxonomy of Hirshleifer-Teoh, 2003).

4.3 The interaction between technical trading and stock price movements

At first I shall discuss the possible interactions between the aggregate trading behavior of technical models and the development of a stock price trends in a stylized manner. Thereby an upward trend is taken as example and three phases of the trend are distinguished according to the positions held by technical models.

The first phase of an upward trend (marked by A and B in figure 5) is usually caused by the excess demand of non-technical traders, triggered off by some economic or political news which lets news-based traders expect a rise of stock prices and, hence, induce them to open long positions in stock index futures.

Figure 5: Stock price trends and aggregate positions of technical models



Over the second phase of an upward trend (between B and C in figure 5) technical models produce a sequence of buy signals, the fastest models at first, the slowest at last. The execution of the trading signals then contributes to the prolongation of the trend. However, this feed-back effect might not be sufficiently strong by itself to let the trend continue due to the transactions of other traders. If, e. g., new information causes news-based traders to switch their positions from long to short then this will turn the price movement from upward to downward (figures 4 shows that the position index increases frequently over some 30-minute-intervals from its local minimum but then falls back again). In many cases, however, technical as well as non-technical traders continue to change their positions from short to long thereby strengthening the upward trend (this reinforcing interaction is depicted in figure 4 by those situations where the net position index moves continuously between -100 to +100).

Over the third phase of an upward price trend most or even all technical models hold long positions (marked by C and E in figure 5). In many cases the trend continues for some time during this phase (figure 4). The longer the trend lasts the more models make profits from the exploitation of the trend. Since technical models already hold a long position the prolongation of an upward trend is caused by an additional demand of non-technical traders. This additional demand might stem from (amateur) "bandwagonists" who jump on price trends later than news-based or technical traders. The transactions of "latecoming bandwagonists" will strengthen the upward movement the more the "market mood" is bullish. If such an expectational bias prevails traders undervalue (or even disregard) news which contradict the bias and overvalue news which confirm the bias (Daniel-Hirshleifer-Subrahmanyam, 1998, model this behavior as "biased self-attribution").

The longer a stock price trend lasts the greater becomes the probability that it ends. This is so for at least four reasons. First, the number of traders who get on the bandwagon declines. Second, the incentive to cash in profits from holding open positions in line with the trend becomes progressively larger. Third, more and more non-technical contrarian traders consider stocks overbought (oversold) and, hence, open a short (long) position in order to profit from the expected reversal of the trend. Fourth, also "fast" contrarian models change their open position once the trend looses momentum.

When the stock price run finally comes to an end, mostly triggered by some economic or political news, a persistent countermovement often takes off (figure 4). With some lag technical models which have not already changed their position start to close the former positions and open new counterpositions (between F and G in figure 5).

For technical stock trading to be overall profitable it is necessary that trends continue for some time after the models have taken long (short) positions. This is so for three reasons. First, all models have to be compensated for the single losses they incur during "whipsaws". Second, fast models often make losses during an "underlying" stock price trend since they react to (very) short-lasting countermovements. Third, slow models open a long (short) position only at a relatively late stage of an upward (downward) trend so that they can exploit the trend successfully only if it continues for some time.

In order to estimate how close stock price movements and the trading behavior of technical models are related to each other the following exercise is carried out. At first, some conditions concerning the change and the level of the net position index are specified. These conditions grasp typical configurations in the aggregate trading behavior of technical models. Then, the difference of the means of the stock price changes observed under these conditions from their unconditional means over the entire sample is evaluated.

The first type of conditions concerns the speed at which technical models switch their open positions from short to long (condition 1L) or from long to short (condition 1S). Condition 1L comprises all cases where 10% (20%, 40%) of all models have been moving monotonically from short to long positions over the past 3 (5, 10) 30-minutes-intervals (all cases are excluded where more than 90% of the models hold long positions - these cases are comprised by condition 2L).

More formally condition 1L is defined as follows.

Condition 1L: $[PI_t\text{-}PI_{t\text{-}i}]>k \cap [PI_{t\text{-}n}\text{-}PI_{t\text{-}n\text{-}1}]\geq 0 \cap [PI_t\leq 80]$

k = 20, 40, 80

i = 3, 5, 10

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

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

Condition 1S: $[PI_t\text{-}PI_{t\text{-}i}]<\text{-}k \cap [PI_{t\text{-}n}\text{-}PI_{t\text{-}n\text{-}1}] \leq 0 \cap [PI_t \geq\text{-}80]$

k = 20, 40, 80

I = 3, 5, 10

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

Condition 2L(S) comprises all cases where more than 90% of all models hold long (short) positions:

Condition 2L(S): PI > 80 (PI < 80)

The diagram gives a graphical representation of the meaning of these four conditions (the subdivision of the conditions 1 and 2, marked by "A" and "B", will be discussed later).

For each trading interval t on which these conditions are fulfilled the rate of change (CSP_t) between the current stock futures price (SP_t) and the respective price j periods (SP_{t+j}) ahead is calculated (j = 5, 10, 20, 40). Then the means over the conditional stock price changes are compared to the unconditional means over the entire sample and the significance of the differences is estimated using the t-statistic. This comparison shall examine if and to what extent stock futures prices continue to rise (fall) after 10% (20%, 40%) of technical models have changed their position from short to long (and vice versa), and if and to what extent this is the case when 90% of all models hold long (short) positions.

For each trading period on which condition 1 is fulfilled also the stock futures price changes over the past i (i = 3, 5, 10) trading intervals are calculated and compared to the unconditional price changes. The purpose of this exercise is to estimate the strength of the simultaneous interaction between stock price movements and technical trading.

Table 4 shows that the conditions 1 are rather frequently fulfilled (S&P trading). E. g., in 11116 (10863) cases more than 10% of all models change their open positions from short to long (from long to short) within 3 periods of 30 minutes (conditions 1L(S) with k=20 and i=3, abbreviated as condition 1L(S)[20/3)]). In 7683 (7263) cases more than 20% of the models change their open position in the same direction within 5 periods. Conditions 1L(S)[80/10] are realized in only 4307 (3969) cases. The number of cases fulfilling conditions 1 are the smaller the larger is the parameter k. E. g., if k=80 then the possible realizations of condition 1L are restricted to a range of the position index between -20 and 90, however, if k=20 then condition 1L could be fulfilled within a range of the position index between -80 and 90.

Conditions 2 occur less frequently than conditions 1. In 7801 cases more than 90% of all models hold a long position (condition 2L). Due to the long-term increase in S&P 500 futures prices between 1983 and 2000 condition 2S was less frequently realized (6959 cases).

Despite the different restrictions imposed on conditions 1L(S) and 2L(S) either of them is fulfilled on 36739 trading intervals out of the entire sample of 62727 trading periods (as regards condition 1 only the cases of conditions 1L(S)[20/3] are considered – most cases satisfying condition 1 with k=40 or k=80 are a subset of the cases satisfying condition 1 with k=20).

The means of the stock index futures price changes (CSP_t) at all points in time satisfying conditions 1 over the <u>past</u> 3 (5,10) 30-minutes-intervals are very much higher than the unconditional means over the entire sample period. E. g., the average (relative) S&P 500 futures price change over 5 consecutive 30-minutes-intervals amounts to 0.015% between 1983 and 2000, however, when 20% of the technical models turn their open position from short to long within 5 intervals the S&P 500 futures price increases on average by 0.63%. This highly significant difference (t-statistic: 85.9) can be attributed to the reinforcing interaction between stock price movements and changing open positions by technical models.

The means of stock price changes over the 5 (10, 20, 40) 30-minutes-intervals <u>following</u> the realization of condition 1 have mostly the same sign as the preceding change in the position index and are in most cases significantly different from the unconditional means. The t-statistics testing for the significance of this difference exceeds 2.0 in 15 out of 24 cases (table 4). However, the t-statistics differs remarkably across the time span j of the ex-ante stock price changes. The means of the price changes over the 5 and 10 trading intervals following the realization of condition 1 have in almost all cases the right sign and are significantly different from the unconditional means. By contrast, over a time horizon of 20 and 40 intervals of 30 minutes (between 1 1/2 and 3 business days) this holds true in only 6 out of 12 cases.

The main reason for this difference lies in the fact that persistent stock price trends on the basis of 30-minutes-data last mostly very short (causing long-term models to perform much worse than short-term and medium-term models – see table 1). This is also the reason why the relationship between the (monotonic) change in open positions and subsequent stock price movements is less close for k=80 as compared to K=20 and k=40 (table 4).

After those 30-minutes-intervals during which 90% of all models hold already a long (short) position (condition 2) stock prices continue to rise (fall) much stronger than on average (table 4). However, this is true only for the first 20 intervals of 30 minutes subsequent to the realization of conditions 2 (the t-statistic is roughly as great as in the case of conditions 1).

Table 4: Aggregate trading signals of 2,580 technical models and stock price movements

S & P 500 futures trading based on 30-minutes-data

Parameters of the conditions for CSP k	i	Time span J of CSP	More than 10% (20%, 40%) of all models change open positions in the same direction within 3 (5, 10) 30-minutes-intervals. From short to long positions (condition 1L): Number of cases	Mean of CSP_{t+j}	t-statistic	From long to short positions (condition 1S): Number of cases	Mean of CSP_{t+j}	t-statistic
20	3	–3	11116	0.422	92.95	10863	– 0.395	– 90.03
		5	11116	0.044	4.79	10863	– 0.008	– 3.58
		10	11116	0.069	4.23	10863	– 0.010	– 4.58
		20	11116	0.078	1.43	10863	0.041	– 1.50
		40	11116	0.154	2.02	10863	0.070	– 2.65
40	5	–5	7683	0.632	85.86	7263	– 0.580	– 92.55
		5	7683	0.049	4.60	7263	– 0.007	– 2.79
		10	7683	0.073	3.97	7263	– 0.010	– 3.80
		20	7683	0.092	2.18	7263	0.051	– 0.54
		40	7683	0.164	2.31	7263	0.072	– 2.11
80	10	–10	4307	0.916	59.27	3969	– 0.782	– 101.43
		5	4307	0.052	4.26	3969	– 0.003	– 1.89
		10	4307	0.056	1.80	3969	0.018	– 0.87
		20	4307	0.110	2.63	3969	0.048	– 0.58
		40	4307	0.158	1.50	3969	0.064	– 1.83
			More than 90% of all models hold the same type of open position. Long positions (condition 2L)			Short positions (condition 2S)		
		5	7801	0.053	4.77	6959	– 0.033	– 3.72
		10	7801	0.067	3.56	6959	– 0.012	– 2.21
		20	7801	0.079	1.36	6959	0.074	0.57
		40	7801	0.066	– 2.57	6959	0.228	3.48

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

Condition 1L (S) comprises all situations where more than 10% (20%, 40%) of all trading systems have been moving monotonically from short to long (long to short) positions over the past 3 (5, 10) trading intervals. The moves are restricted to a range of the position index PI_t between 80 and –80.

Condition 2L (S) comprises all situations beyond this range, i.e., where more than 90% of all trading systems hold long (short) positions.

More formally these conditions are defined as follows:

Condition 1L (S): $[PI_t - PI_{t-1}] > k\ (< -k) \cap [PI_{t-n} - PI_{t-n-1}] \geq 0\ (\leq\ 0) \cap [-80 \leq PI_t \leq 80]$

k 20, 40, 80

i 3, 5, 10

n .... 0, 1, ... (i – 1)

Condition 2L (S): $PI > 80\ (< -80)$

$CSP_{t+j} = 100 * [SP_{t+j} - SP_t] / SP_t$ for j 5, 10, 20, 40

$CSP_{t+j} = 100 * [SP_t - SP_{t+j}] / SP_t$ for j .... –5

The t-statistic tests for the significance of the difference between the mean of the conditional exchange rate changes and the unconditional mean over the entire sample, the latter being as follows:

For j = 3	0.0090
5	0.0149
10	0.0297
20	0.0593
40	0.1171

Since (almost) all technical models are already holding positions congruent with the direction of a stock price trend its continuation must be attributed to the transactions of non-technical traders.[7]) These "latecoming bandwagonists" (perhaps amateurs) continue to exert an excess demand on the market. Their behavior lengthen stock price trends and, hence, cause technical models to be overall profitable. These "latecomers" are probably also the most important losers in stock futures trading, even though they can hardly be identified, in part because the "membership" to this group strongly fluctuates (due to the trading losses).[8])

Over time spans of 20 and 40 trading intervals after 90% of all models hold already a long (short) position (condition 2) price changes differ only insignificantly from the unconditional means or have even the wrong sign. E. g., stock prices fall (rise) over the 40 intervals following the realization of condition 2L(S) significantly stronger than on average. This relationship implies that stock index futures prices based on 30-minutes-data are mean-reverting over relatively short time horizons. This result is in line with two findings of the profitability tests based on 30-minutes-data, namely, that short term trading systems perform best, and that contrarian models perform better than trend-following models (Schulmeister, 2007B).

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=40 and i=5). The meaning of the (sub)conditions A and B is explained as follows, taking an upward trend as example (figure 5).

Condition 1LA comprises all cases where 20% of all models have changed their positions from long to short and where at the same time still less than 50% of the models hold long positions. Hence, condition 1LA covers the first phase of reversing technical positions after stock prices have started to rise (all cases under condition 1LA lie below the zero level of the position index – see figure 5).

Condition 1LB comprises the second phase of position changes, e. g., when a stock price trends has gained momentum so that already more that 50% of the models are holding long positions.

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[7]) It is highly unprobable that slower models than the slowest models included in this study are actually used in practice when S&P 500 futures trading is based on 30-minutes-prices. This is so because the slowest models investigated perform worse than the other models included in this study. This result holds true also for each of six subperiods between 1983 and 2000 (Schulmeister, 2007B). Hence, it would have been easy for a technical trader to discover this fact.

[8]) 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.

Condition 2LA covers the third phase in the trading behavior of technical models during an upward trend, namely, the first 5 30-minutes-intervals after more than 90% of all models have opened and are still holding long positions.

Condition 2LB comprises the other 30-minutes-intervals over which 90% of all models keep holding long positions, i.e., the fourth and last phase which endures until the models start to again reverse their position in reaction to a downward movement.

Table 5: Eight phases of technical trading and stock price movements
All models
S & P 500 futures trading based on 30-minutes-data

Conditions for CSP_{t+j} (= Phase of technical trading)	Time span j of CSP_{t+j}	(Increasing) Long positions (conditions .L.)			(Increasing) Short positions (conditions .S.)		
		Number of cases	Mean of CSP_{t+j}	t-statistics	Number of cases	Mean of CSP_{t+j}	t-statistics
1A	5	1972	0.047	1.88	5327	– 0.016	– 3.83
1B	5	5711	0.049	4.52	1936	0.018	0.16
2A	5	6157	0.073	6.23	5666	– 0.049	– 6.01
2B	5	1644	– 0.020	– 2.57	1293	0.038	0.47
1A	10	1972	0.105	3.38	5327	– 0.016	– 3.96
1B	10	5711	0.062	2.66	1936	0.006	– 1.09
2A	10	6157	0.095	5.39	5666	– 0.049	– 5.09
2B	10	1644	– 0.036	– 3.58	1293	0.153	1.68
1A	20	1972	0.133	2.43	5327	0.048	– 0.65
1B	20	5711	0.078	1.11	1936	0.060	0.01
2A	20	6157	0.117	3.61	5666	– 0.003	– 2.63
2B	20	1644	– 0.065	– 4.53	1293	0.410	3.86
1A	40	1972	0.226	2.65	5327	0.088	– 1.16
1B	40	5711	0.143	1.13	1936	0.027	– 2.35
2A	40	6157	0.076	– 1.83	5666	0.137	0.62
2B	40	1644	0.030	– 2.39	1293	0.624	5.73

Each of the four phases of technical trading defined by the conditions 1L (S) and the conditions 2L (S) for k = 40 and i = 5 (see table 4) is divided into two subphases by the conditions A and B:

Condition 1L (S): More than 20% of all trading systems have been moving from short to long (long to short) positions over the past five 30-minutes-intervals within the range $\{-80 \leq PI_t \leq 80\}$ and ....

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

Condition 1L (S) B: More than 50% of the models holg long (short) positions, i.e., $PI_t \geq 0$ ($PI_t \leq 0$).

Condition 2L (S): More than 90% of all trading systems hold long (short) positions, i.e., $PI_t > 80$ ($PI_t < -80$).

Condition 2L (S) A: Comprises the first five 30-minutes-intervals for which condition 2L (S) holds true.

Condition 2L (S) B: Comprises the other 30-minutes-intervals for which condition 2L (S) holds true.

The t-statistics tests for the significance of the difference between the mean of the conditional stock price changes and the unconditional mean over the entire sample (see table 4).

Condition 1LA is much less frequently realized than condition 1LB, the opposite is true as regards conditions 1SB and 1SB (the number of realizations of conditions 1L and 1S is roughly the same – table 5). These differences might be due to the long-term increase in stock prices between 1983 and 2000, if this increase had been realized in such a way that upward movements lasted longer than downward movements, the latter being at the same time steeper than the former (such a pattern was typical for the appreciation process of the dollar between 1980 and 1985 – Schulmeister, 1987 and 1988).

Table 5 shows that the size of the conditional ex-ante stock futures price changes differs across the four conditions 1LA, 1LB, 2LA and 2LB. The average rise of the S&P 500 futures price following the realizations of condition 1LA, is significantly higher than the unconditional price changes over all 4 time spans. The increase in stock prices following condition 1LB is in most cases smaller than under condition 1LA (price movements often loose persistence after a first "take-off").

The average rise of stock prices is most significantly different from the unconditional mean following the realizations of condition 2LA, e. g., during the first 5 intervals after 90% of all models have taken long positions (except for the subsequent price changes over a time span of 40 intervals) Stock price changes subsequent to the realizations of condition 2LB are significantly negative. This result reflects the trend-reverting behavior of stock price movements. Hence, stock price changes in the late phase of an upward trend will mostly be negative.

These results hold also true for the conditional ex-ante stock futures price changes in the case of downward trends (conditions 1SA, 1SB, 2SA and 2SB). Over a time horizon of 20 and 40 days trend reversals after downward movements are even more pronounced as compared to trend reversals following upward trends. This difference is most probably related to the fact that S&P 500 futures prices strongly increased over the long run between 1983 and 2000.

5. Summary and concluding remarks

This study investigated the interaction between the aggregate trading behavior of 2580 technical trading systems and S&P 500 futures prices based on 30-minutes-data between 1983 and 2000. The main results are as follows:

- When technical models produce trading signals, almost all signals are on the same side of the market, either buying or selling. When they hold open positions they are either long or short. Hence, the aggregate trading behavior of technical models exerts an excess demand pressure on the stock market.
- A strong feed-back mechanism operates between stock price movements and the transactions of technical models. Rising (falling) stock prices cause increasingly more

trend-following models to produce buy (sell) signals, which in turn strengthen and lengthen the trend.

- After a certain portion of technical models has reversed their open positions, stock prices continue to move in the direction congruent with the initial position holding.
- After 90% of the models have already changed their open positions from short to long (long to short) stock prices continue to rise (fall) over the subsequent five to ten 30-minutes-intervals. Thereafter, stock price trends tend to change their direction.
- The continuation of stock price trends after most technical models have opened positions congruent with the trend has to be attributed to the transactions of non-technical traders, perhaps amateurs. At the same time, these "latecoming bandwagonists" are probably the most important losers in short-term futures trading.

Finally, I would like to relate the results of this study, as well as of the complementary profitability study (Schulmeister, 2007B) to the concepts of market efficiency and rational behavior.

The efficient market hypothesis holds that utility maximizing agents form their expectations "rationally," e.g., according to the true (capital asset pricing) model. According to this view, prices fully reflect all available information at every point in time. Consequently, trading strategies that use only the information contained in current and past prices are unable to consistently deliver profits (Fama, 1970, 1998).

The concept of technical analysis and its use in practice are in sharp contrast to the efficient market hypothesis. Technical models disregard market fundamentals. Instead, they use only the information contained in past prices to identify the direction of persistent price trends (technical trading does not imply any kind of quantitative price expectation). However, this study shows that technical stock futures trading would have been consistently profitable. Since the aggregate transactions and positions of technical models exert an excess demand (supply) on the market, the use of these models is destabilizing and profitable at the same time (in contrast to the classical argument of Friedman, 1953).

Whether technical trading is irrational or rational, in the sense that it enables one to earn extra profits, can only be judged on empirical grounds. If asset prices often move in trends which can be profitably exploited by technical trading, then following these strategies should not be considered irrational. At the same time, the widespread use of technical trading systems feeds back upon the persistence of asset price trends. This study showed that price trends tend to continue for some time after technical models have already taken the "right" position in the market. Hence, the last phase of a price trend (which is essential for technical trading to be profitable) is brought about by the transactions of non-technical noise traders. This means that technical traders follow the same strategy as those rational speculators in the "noise trader approach" who anticipate the behavior of noise traders and exploit it at the same time (in the widely-cited study by DeLong-Shleifer-Summers-Waldmann, 1990B, it is the rational speculators who strengthen or even cause trends by anticipating the feed-back traders).

As regards the concept of rationality, one has to keep in mind that the meaning of this concept depends on the assumptions made about the "state of the world". Hence, any judgment about the (ir)rationality of technical trading is context-dependent:

- If one assumes that market participants are risk neutral, possess perfect knowledge, and unlimited resources, then technical trading would be quickly wiped out by the rational speculators (this is the rational expectations view).
- 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 not profitable and irrational (this is the behavioral finance view).
- If one assumes that human knowledge is essentially imperfect - no one has access to the true model - that perceptions of the world are thereby heterogeneous, that trading decisions are governed not only by reason, but by emotions which are "bundled" through social interaction into "market moods," then asset prices will tend to fluctuate in a sequence of trends (this is the "imperfect knowledge economics" view of Frydman-Goldberg, 2007). In such a world, technical trading is a reasonable (rational) strategy for coping with ever-imperfect knowledge.

The results of this study suggest that future research on asset price dynamics should consider the "imperfect knowledge economics" view as an alternative conception to the rational expectations view as well as to the behavioral finance views.

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