CHRISTIAN JOCHUM*

Does Market Momentum survive longer than it should?

1. Introduction

Recent evidence produced by FUNG/HSIEH (1997a, 1997b) for Hedge funds and CTAs and by GRINBLATT/TITMAN/WERMERS (1995) for Mutual funds shows that a significant portion of money managers tend to follow investment strategies that reflect the asset's past performance. That is, money managers follow market and security price trends in their investment decisions. This type of behavior does contradict the assumptions underlying the efficient market model that is usually employed to describe the price building process on the financial markets. Consequently, these investment strategies should not be able to provide the investor with satisfactory returns. But GRINBLATT et al. provide evidence that trend following strategies are able to outperform a basic buy and hold strategy and also offer better returns than a contrarian approach.[1] Using a cross-section approach, ROUWENHORST (1998) shows for a sample of international markets that as a result of return continuation past winners tend to outperform past losers after adjusting for risk.

The question whether momentum strategies offer a useful instrument in the investment decision making process can also be answered by addressing the following simple question: Based on past positive (negative) returns, is a positive (negative) return today more likely than simple chance would imply? We address this question using daily stock market data from three of the major financial centers: London, New York, Zurich. While all three markets provide sufficient liquidity to allow for efficient information processing, they nevertheless represent different size categories, such that the results below do not represent idiosyncratic characteristics of one market (size). In order to answer the above question a measure is employed that describes the likelihood that an existing trend will persist beyond the present date. For that purpose we calculate so called survival functions in the form of the KAPLAN-MEIER estimator. The respective probabilities that a trend will continue are then compared to the probabilities implied by simulated stock price series. These simulations are based on three commonly used processes in the description of stock price movements: a Random Walk with drift, an ARMA pro-

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cess, and an EGARCH model. The results of the comparison show that particularly upwards trends have a significantly better chance to persist that the simulations would imply. This means that the markets exhibit more complex pattern than are reflected in the simulation models. To the extend that momentum (trend following) strategies are able to exploit these nonlinearities will fund managers be able to 'beat the market'.

2. Determining momentum

As a first step the concept of momentum has to be formalized, which, as NEFTCI (1991) shows for a number of other technical trading strategies, can be problematic, because technical strategies, e.g. momentum, are usually not well defined. In the context of this study this problem translates into the choice of a particular momentum definition and emphasis that the same definition is employed to both the market and the simulated series.

The procedure used to assign the daily changes in the stock market index to either a positive trend, a negative trend or a period without trend is as follows: The minimum requirement for consecutive changes to be considered relevant for the observation of momentum is a same sign change on at least two consecutive trading days. Additional and immediately following price changes of the same sign are then added to the calculation of the duration of this particular momentum event. A trend is considered to be broken by any price change that has the opposite sign to the sign of the current trend. This construction implies that positive and negative momentum periods do not necessarily alternate but that a trend may be followed either by a reverse trend or a trendless period, which may then be followed by another trend of either sign. To allow for the occurrence of (small) 'technical' corrections, i.e. a negative price change in an upward trend, the above rule has been relaxed in the following way: Provided that at least 2 consecutive positive (negative) trend signals have been generated, a negative (positive) price change does not interrupt the prevailing trend as long as it is smaller than half the current return standard deviation[2] and is followed by a price change that supports the present positive (negative) trend. Table 1 shows the assignments of a series of fictional price changes to either a positive or negative trend: the shortest possible trend consists of 2 observations, and, as observation 10 shows, some sign changes are not considered large enough to signal a break in market momentum.

For each trend the number of days it persisted is recorded, in the process providing the information of how many trends had a duration of e.g. 5 or 10 days and what the direction of the trend was. By means of the KAPLAN-MEIER estimator this information is then used to calculate the (survival) probability of a positive (negative) trend to last, e.g., 5 or 10 days.

Table 1: Price changes and trend construction (example)

Day	1	2	3	4	5	6	7	8	9	10	11	12	13
Price Change	0.30	−1.65	−0.87	−0.90	0.44	−0.65	0.13	0.48	0.16	−0.03	0.90	1.10	−0.87
Pos. Trend	0.00	0.00	0.00	0.00	0.00	0.00	+1.0	+1.0	+1.0	+1.0	+1.0	+1.0	0.00
Neg. Trend	0.00	−1.0	−1.0	−1.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

2.1 KAPLAN-MEIER estimator

The KAPLAN-MEIER (K-M) estimator of a survival function[3] is the censored data generalization of the empirical distribution function, where the survival function $P(X_i > t)$ describes the probability that an individual (product, behavior) is still alive (working, present) after t periods. Additionally, the estimator allows the determination of the probability of an individual of not surviving a particular time period, given that not all individuals in the sample died during the observation period (i.e. before the censoring date). The survival function for time t can be calculated as

$$\hat{S}(t) = \prod_{j:t(j)\le t} \left(1 - \frac{d_j}{n_j}\right) \tag{1}$$

where t(j) denotes the ordered failures at times t = t(j): $t(1) \le t(2) \le \ldots \le t(k)$, d_j describes the number of failures at time t = t(j), and n_j denotes the number of items still alive just before period t = t(j). Following this definition the K-M estimator takes the form of a step function with steps at times t, where a loss of an item occurs. If the results are censored at t(k), the function takes a horizontal form for items surviving beyond t = t(k). An estimator of the variance of the K-M estimator $S(t)$ at a specified time t is given by

$$\text{Var}\,(\hat{S}(t)) = \hat{S}^2(t) \sum_{t(j)\le t} \frac{d_j}{n_j(n_j - d_j)} \tag{2}$$

Thus the K-M estimator provides a means to determine the likelihood that a particular item is still present at some time t and allows to calculate the statistical significance of that event.

3. Simulating stock price processes

The empirical survival function is compared to the survival functions based on the simulation of three widely used processes for the description of stock price behavior: a Random Walk with drift, an ARMA(1,1) process including a nonzero constant, and an AR(1)-EGARCH model. While the Random Walk (with drift) behavior of the market is implied by the efficient market literature, the ARMA(1,1) model has proven very successful in the description of financial time series (PAGAN, 1996), because it allows for the reported tendency of returns to show significant autocorrelation over short periods. While the Random Walk with drift is defined by the descriptive statistics of the return sample, the ARMA(1,1) is given by

$$r_t = cc + a_1 \cdot r_{t-1} + a_2 \cdot v_{t-1} + v_t \tag{3}$$

where r is the market return, and the inclusion of a constant cc allows for a nonzero mean in the process.

Although the basic GARCH model captures most of the major characteristics of financial market data, FRENCH/SCHWERT/STAMBAUGH (1987) confirm previous results that additional asymmetric leverage effects are usually found in stock market data. The EGARCH specification (NELSON, 1991) adds this nonlinear component to the model of the market behavior:

$$r_t = \alpha_1 + \alpha_2 \cdot r_{t-1} + \varepsilon_t$$

$$\log(\sigma_t) = \omega + \beta_1 \cdot \log(\sigma_{t-1}) + \beta_2 \cdot \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}} + \beta_3 \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}}} - \sqrt{2/\pi} \right] \tag{4}$$

To confirm the asymmetry assumed in the data, the coefficient β_2 should be negative.

The Monte Carlo simulation of these processes is based on the parameter estimates using the complete sample of data available and produces 600 new price series[4], consisting of 6500 observations each. For these price series the survival statistics are calculated and it is tested whether there is a statistical difference between the simulated results and the results gained from the market price series. That is, we test the hypothesis whether the empirical survival probability $\hat{S}(t)$ is smaller than (or equal to) the simulated survival probability

$$S^*(t): H_0: = [\hat{S}(t) - S^*(t)] \leq 0 .$$

This comparison allows inference with respect to two related questions: (1) If the probability of survival of an existing trend is higher than the values gained for a Random Walk with drift, then the markets show more momentum than predicted by the efficient market literature and momentum strategies may yield positive returns; (2) if this null hypothesis can also be rejected with respect to the ARMA(1,1) and/or the AR-EGARCH model, then these models also do not allow for the full complexity of the price generating process.

4. The Data

Daily closing prices of 3 major stock markets are used for the estimation: London, New York and Zurich. The data have been collected from DATASTREAM. The Swiss market index (SMI) is replaced by the Vontobel index, which is available for a considerable longer period than the relatively new SMI. Each of these series contains 6523 observations between January 1973 and December 1997 and describes periods of major changes in the economies and the financial markets: the period of high interest rates in the early eighties, the crash of 1987 and the subsequent build-up in stock prices, and more examples of significant developments in the financial markets.

The data for all markets show positive average returns and, compared to the mean, large standard

Table 2: Descriptive statistics

Daily stock market returns (in %) for Zurich (Zu), London (Lo) and New York (NY) from January 1, 1973 to December 31, 1997: 6523 observations. Returns are in local currency.

	mean	std. dev.	minimum	maximum	ARCH(20)
London	0.037	1.002	–12.117	8.943	1869.9**
New York	0.031	0.994	–25.631	9.666	292.13**
Zurich	0.025	0.793	–11.948	5.948	1188.3**

	positive returns		negative returns	
	mean	std. dev.	mean	std. dev
London	0.709	0.694	–0.730	0.754
New York	0.710	0.659	–0.696	0.798
Zurich	0.519	0.521	–0.548	0.697

The test for the presence of ARCH follows ENGLE (1982) by testing that the coefficients from the regression of the squared residual on its past values are jointly 0: $\varepsilon_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \cdots + \beta_n \varepsilon_{t-n}^2$. The test statistic is a Chi square. 'positive returns' and 'negative returns' refers to the respective sub-samples.

Table 3: Parameter estimates: London, New York, Zurich

Panel A	Coefficient estimate for a Random Walk with drift	Coefficient estimates for a ARMA(1,1) model		
Stock market	d	cc	a_1	a_2
London	0.0248	0.037	0.088	0.089
		(0.01)**	(0.07)	(0.07)
New York	0.0368	0.031	–0.441	0.506
		(0.01)*	(0.13)**	(0.12)**
Zurich	0.0310	0.025	0.163	–0.053
		(0.01)*	(0.11)	(0.00)**

Panel B	Coefficient estimates for an EGARCH model					
Stock market	α_1	α_2	ω	β_1	β_2	β_3
London	0.037	0.158	–0.001	0.983	–0.029	0.179
	(0.01)**	(0.01)**	(0.01)	(0.01)**	(0.00)**	(0.01)**
New York	0.029	0.072	0.002	0.980	–0.052	0.129
	0.01)**	(0.01)**	(0.00)*	(0.00)**	(0.01)**	(0.01)**
Zurich	0.027	0.208	–0.015	0.957	–0.068	0.234
	(0.01)**	(0.01)**	(0.00)**	(0.00)**	(0.00)**	(0.00)**

Standard errors in brackets. *, ** indicate 5% and 1% level of significance.

deviations. These high measures of dispersion can be attributed to the high frequency of large (negative) outliers. The return series all show a significant rejection of the null hypothesis that ARCH effects are not present in the data. Splitting the underlying samples into subsets defined by positive and negative returns shows that the dispersion of negative returns is indeed larger than the dispersion of the positive returns, but that the absolute mean returns remain in a close range.

5. Results

5.1 Model Estimation

Table 3 presents the parameter estimates for the three stock markets and the respective models. For the Random Walk the average (daily) change in the stock price is taken as proxy for the drift term. The coefficients on the ARMA(1,1) model show a varying degree of significance, while the parameters of the EGARCH model take the expected values; particularly the coefficient β_2 is significant and negative, which indicates that an unexpected negative return increases the subsequent volatility more than an unexpected positive return of the same size. These parameter estimates are now used to generate simulated return series. The values of the survival functions derived for these series are then compared to the survival probabilities of the actual market price series, and it is tested whether the market probabilities are lower than the statistics for the simulated series.

5.2 Empirical survival probabilities and simulation

Table 4 shows the step by step calculation of the KAPLAN-MEIER estimator using data for the London market. Looking at positive momentum,

Table 4: KAPLAN-MEIER estimator – London

Estimator of the survival function of positive market momentum

	ordered failure time	intact before t	ending at time t	contribution to K-M estimator	K-M estimator	Variance
j	t(j)	n_j	d_j	$(1-(d_j/n_j))$	S(t)	Var (S(t))
1	2	687	113	0.835	0.835	0.00020
2	3	574	194	0.662	0.553	0.00035
3	4	380	127	0.666	0.368	0.00038
4	5	253	73	0.711	0.262	0.00028
5	6	180	52	0.711	0.186	0.00020
6	7	128	44	0.656	0.122	0.00016
7	8	84	23	0.726	0.088	0.00011
8	9	61	19	0.688	0.061	0.00008
9	10	42	13	0.690	0.042	0.00006
10	11	29	5	0.827	0.035	0.00005
11	12	24	12	0.500	0.017	0.00003
12	13	12	6	0.500	0.008	0.00001
13	14	6	3	0.500	0.004	0.00000
14	16	3	3	0.000	0.000	

n_j and d_j are the number of trends lasting up to time t(j), failing at time t(j). $(1-(d_j/n_j))$ and S(t) are probabilities describing the likelihood of survival at time t(j) and beyond t(j).

the first failure time (i.e. when a trend breaks) occurs, by construction, at t = 2. Proceeding from there we find that for the London market the longest sequence of price changes that satisfies the momentum definition above lasted 16 days. This occurred three times over the sample period, while 5 day upward trends occurred 73 times and 10 day trends still occurred 13 times.

The contribution to the K-M estimator $(1 - (d_j/n_j))$ can be interpreted as the per-period probability that the trend will continue. That is, for a 3 day trend we face a probability of 66.2% that the trend will not stop at that day but continue and it can be seen that up till day 11 the per period survival probability roughly stays at that level. Finally, the K-M column presents the probability that a trend lasts beyond t days: we find a 37% chance that a trend persists for at least 5 days, a 6% chance that a trend lasts 10 days and, based on this sample, a 0.0% chance for a trend to last longer than 16 days. The variance estimates for the K-M estimator are all low enough, such that the statistical significance of the survival probabilities is not endangered.

Table 5 presents the empirical survival functions for positive and negative momentum on the London, New York and Zurich stock market, that is the probability that a trend has a duration longer than t = t(j). The first column of table 5 is similar to the K-M column presented in table 4. The statistics show that market momentum in an upward moving market is stronger than in a falling market, since for all markets the positive trend probabilities are higher than their negative counterparts.[5] Also, on average, negative trends tend to be shorter than positive ones. In terms of the individ-

Table 5: Empirical survival function: London, New York, Zurich
Empirical (K-M) survival functions for market momentum (positive and negative)

	London		New York		Zurich	
t(j)	positive	negative	positive	negative	positive	negative
2	0.835	0.796	0.794	0.760	0.838	0.783
3	0.553	0.469	0.466	0.436	0.510	0.456
4	0.368	0.291	0.289	0.264	0.363	0.298
5	0.262	0.192	0.203	0.165	0.264	0.207
6	0.186	0.131	0.126	0.093	0.194	0.139
7	0.122	0.077	0.072	0.049	0.150	0.085
8	0.088	0.045	0.047	0.030	0.116	0.054
9	0.061	0.026	0.029	0.019	0.077	0.034
10	0.042	0.015	0.017	0.010	0.052	0.017
11	0.035	0.011	0.005	0.003	0.035	0.009
12	0.017	0.003	0.000	0.000	0.030	0.007
13	0.008	0.000			0.024	0.003
14	0.004				0.009	0.000
15	0.004				0.006	
16	0.000				0.000	

The columns describe the (empirical) probability that a market trend will continue beyond time t = t(j).

ual markets, New York shows considerable less persistence in its market moves than either London or Zurich, with the latter[6] being the market with the highest degree of positive momentum and an average probability difference to New York of 6–8%. The gap between the calculated probabilities in New York versus London and Zurich is smaller for negative market movements, but the chance of a negative trend persisting in New York is still on average 3% lower than in the other two markets.

These (empirical) probabilities on the markets of London, New York, and Zurich are now compared to the probabilities that can be calculated for the simulated series. If the models underlying the simulation are sufficient to mirror the behavior of the stock market then no statistically significant difference in the survival probabilities is expected. The values describing the simulated series are presented in tables 6a – c.

One finds that, particularly for the London and Zurich market, there is a significant gap between the market probability of survival and the probabilities implied by the simulation models. The asterisks beside the probabilities describe the level of significance at which the hypothesis that the empirical survival probability is smaller than (or equal to) the simulated probability can be rejected. At the London market the probability of a market trend to survive is significantly higher than implied by a Random Walk (RW) with drift until the 12^{th} day for a positive trend and up till the 9^{th} day for a negative trend. While the survival probability calculated for an ARMA process is too low over 11 days for a positive trend, the model generates sufficient dynamics to capture most of the downward momentum in the market. While the EGARCH model is most successful in simulating the market behavior, there is still significant upward momentum not accounted for.

Table 6a: Trend simulation (London)
Probability that a simulated trend will continue: London.

	RW + drift		ARMA(1,1)		EGARCH	
t(j)	positive	negative	positive	negative	positive	negative
2	**0.703****	**0.678****	**0.750****	**0.726****	**0.759****	**0.731****
3	**0.412****	**0.375****	**0.477****	**0.439**	**0.486****	**0.437***
4	**0.262****	**0.227****	**0.322****	**0.284**	**0.331***	**0.281**
5	**0.169****	**0.140****	**0.221****	**0.187**	0.231*	**0.185**
6	**0.107****	**0.085****	**0.150****	**0.121**	0.160*	**0.120**
7	**0.068****	**0.051****	**0.100***	**0.078**	0.110	**0.077**
8	**0.043****	**0.031***	**0.067***	0.050	0.074(*)	0.050
9	**0.027****	**0.018**(*)	0.045*	0.032	0.051	0.032
10	**0.017****	**0.011**	**0.030***	0.020	0.034	0.021
11	**0.010****	**0.006**(*)	0.020**	0.013	0.023*	0.013
12	0.006*	0.004	0.012	0.008	0.015	0.008
13	0.004	0.002	0.008	0.005	0.001	0.005
14	0.002	0.001	0.005	0.003	0.001	0.003
15	0.001	0.001	0.002	0.002	0.000	0.002
16	0.001	0.001	0.001	0.001	0.000	0.001
17	0.000	0.000	0.000	0.000	0.000	0.000

The columns describe the (simulated) probability that a trend will continue beyond time t = t(j). **, *, (*) indicate that the hypothesis that the market probability is smaller than (or equal to) the simulated probability can be rejected at the 1, 5, 10% level. Values marked "bold" indicate a rejection of the null-hypothesis, at least at the 10% level, using de-meaned data.

The New York market is more 'efficient' than the other two markets in the sense that all models are better able to capture the dynamics of the (empirical) return series. This implies that momentum generally is less pronounced for this market than for the smaller London and Zurich market. But the New York market still shows a greater tendency to produce (positive) same sign changes than one would expect if the underlying market process was a Random Walk with drift or an ARMA process. Only the EGARCH model comes close to capturing the complete set of market dynamics. Compared to the results found for the New York market, the Zurich market shows a particularly more pronounced tendency to exhibit market momentum. Positive trends are more frequent than indicated by a RW or an ARMA process up to 14 trading days, and up to 12 trading days if compared to the EGARCH simulations. The test statistics on the EGARCH model show a gap at days 3 and 4, where the empirical probability of a trend to finish during one of these two days is higher than the simulated probability. But this is compensated for by the high (per period) survival probability during day 2 and the days following day 4, such that the probability to reach trend lengths up to 12 days remains too high. The described effects are again less pronounced for the down side of the market, but the degree of momentum in the market is still higher than in the simulated series.

Table 6b: Trend simulation (New York)
Probability that a simulated trend will continue: New York.

	RW + drift		ARMA(1,1)		EGARCH	
t(j)	positive	negative	positive	negative	positive	negative
2	**0.701****	**0.680****	**0.701****	**0.689****	**0.728****	**0.704****
3	**0.407****	**0.377****	**0.417****	**0.396****	0.443	**0.404**(*)
4	**0.256****	**0.229***	0.267*	**0.247**	0.290	**0.252**
5	**0.165****	**0.142***	**0.174***	**0.157**	0.195	**0.161**
6	**0.103***	**0.086**(*)	0.111	**0.097**	0.129	0.100
7	0.065	**0.051**	0.071	0.060	0.085	0.062
8	0.040	0.031	0.045	0.037	0.057	0.038
9	0.024	0.018	0.029	0.023	0.038	0.024
10	0.014	0.010	0.018	0.014	0.025	0.014
11	0.008	0.005	0.011	0.008	0.016	0.009
12	0.004	0.003	0.007	0.005	0.010	0.005
13	0.002	0.001	0.004	0.003	0.001	0.003
14	0.000	0.000	0.002	0.002	0.001	0.002
15	0.000	0.000	0.001	0.001	0.001	0.001
16	0.000	0.000	0.001	0.001	0.001	0.001
17	0.000	0.000	0.000	0.000	0.000	0.000

The columns describe the (simulated) probability that a trend will continue beyond time t = t(j). **, *, (*) indicate that the hypothesis that the market probability is smaller than (or equal to) the simulated probability can be rejected at the 1, 5, 10% level. Values marked "bold" indicate a rejection of the null-hypothesis, at least at the 10% level, using de-meaned data.

Table 6c: Trend simulation (Zurich)
Probability that a simulated trend will continue: Zurich.

	RW + drift		ARMA(1,1)		EGARCH	
t(j)	positive	negative	positive	negative	positive	negative
2	**0.702****	**0.680****	**0.735****	**0.713****	**0.771****	0.742**
3	**0.409****	**0.377****	**0.456****	**0.420***	0.503	0.456
4	**0.259****	**0.223****	**0.302****	**0.266***	0.347	0.298
5	**0.167****	**0.143****	**0.204****	**0.172****	0.245(*)	0.198
6	**0.106****	**0.086****	**0.136****	**0.110****	**0.171***	0.130
7	**0.067****	**0.052****	**0.089****	0.070(*)	**0.119****	0.085
8	**0.043****	**0.032****	**0.059****	0.044	**0.082****	0.056
9	**0.027****	**0.019****	**0.039****	0.028	**0.058***	0.036
10	**0.017****	0.011*	**0.025****	0.018	**0.040**(*)	0.024
11	**0.010****	0.007(*)	**0.016****	0.011	0.027*	0.015
12	**0.006****	0.004(*)	**0.010****	0.007	0.018**	0.009
13	**0.004****	0.002	**0.006****	0.004	0.012	0.006
14	**0.002****	0.001	**0.004****	0.002	0.007	0.003
15	0.001	0.001	0.002	0.001	0.004	0.002
16	0.001	0.001	0.001	0.001	0.002	0.001
17	0.000	0.000	0.000	0.000	0.000	0.000

The columns describe the (simulated) probability that a trend will continue beyond time t = t(j). **, *, (*) indicate that the hypothesis that the market probability is smaller than (or equal to) the simulated probability can be rejected at the 1, 5, 10% level. Values marked "bold" indicate a rejection of the null-hypothesis, at least at the 10% level, using de-meaned data.

5.3 Interpreting the results

We find for all three markets that the implicit (efficient market) hypothesis that stock price changes are governed by a Random Walk (with drift) does not find support by the results presented here. Additionally, even relatively complex models for market behavior as an EGARCH are not able to fully capture the dynamics in the empirical price series. This insight is in agreement with results presented by NEFTCI (1991) and BROCK/LAKONISHOK/LEBARON (1992) who find that financial markets show a higher degree of complexity than is taken account of by the usually employed market models. For the same reason these authors conclude that investment strategies based on relatively simple (technical) trading rules can yield positive investment returns.

All of which leaves us with the troubling question, why this profit opportunity is not arbitraged away. Closely linked to this issue is the question how trends in asset prices originate in the first place. The traditional finance literature sees the reasons for autocorrelation in the gradual release of information and the tendency of the market to take time to "digest" news. Both points allow to uphold the central creed of the efficient market literature, namely that at each point the price reflects the best interpretation of the available fundamental information on the respective asset. Consequently, investment strategies that rely on the detection of trends, e.g. technical analysis, remain unprofitable.

This view has over the past years been challenged by the rapidly expanding field of behavioral finance, which aims to explain investor behavior as a psychological and social activity.[7] To the degree that investors are subject to herding behavior or to the tendency to falsely see price patterns, asset valuations can and will deviate from fundamentals over considerable periods of time, generating positive and/or negative trends in the process.

As shown by SHLEIFER/VISHNY (1997) it is possible that the existence of a group of traders, who react on past price changes, creates price movements that deviate from fundamentals but cannot be arbitraged away as long as the arbitrageur does not have unlimited resources at his disposal. Consequently, continued deviations from fundamentals can persist in a market, because risk averse (fundamentals) investors are aware that their funds will potentially be wiped out before markets have corrected, and hence they will abstain from betting against the trend.[8] This generates a market environment, where noise traders actually find sufficient return to justify their trading strategies.[9]

Summarizing, two sources for trends in asset prices are identified, information processing and the existence of investment behavior that leads prices away from fundamentals. It has also been noted that arbitrage, unless unlimited, is not sufficient to stop trends as they occur. Both sources, but particularly noise trading, generate non-linear price patters that are not fully picked up by the traditional empirical models employed to describe financial time series. This insight is underlined by the results presented here.

6. Conclusion

Money managers use strategies that rely on the continuation of existing trends. The results presented indicate that, contrary to the conclusions of the efficient market model, this behavior may be able to exploit (ir)regularities in the stock price process. The probability of an upward (or downward) trend to continue is too high to be explained by a number of commonly used return generating models. The tendency of momentum to persist is more pronounced for upward movements of the market than for sell periods and is generally less pronounced for the New York market than for the other two markets investigated.

Footnotes

[1] Also, ASNESS, LIEW, and STEVENS (1997) find that markets (and stocks) with upward momentum yield higher average returns and that winners continue to outperform losers. KIM, NELSON, and STARTZ (1991) show that for post-war data there is a tendency towards persistence in returns and report positive autocorrelation. This result is corroborated by CAMPBELL, LO, and MACKINLEY (1997), who find significant positive autocorrelation in daily stock return data.

[2] For the return series investigated the standard deviation is calculated for the observations available up to the date of the trend signal. Hence it shows a limited amount of variation through time. On average, the time-varying standard deviation is between 0.9–1.1%. A change of the criterion to a full standard deviation does not affect the results presented, but it seems more likely that the markets consider a 0.45–0.55% correction 'small' and not an interruption of an existing trend.

[3] For a survey of the economic literature employing the concept of hazard (survival) functions, see KIEFER (1988). For a presentation of the KAPLAN-MEIER estimator, see KOTZ, JOHNSON, and READ (1983).

[4] BROCK, LAKONISHOK, and LEBARON (1992) show that using more than 500 replications does add little to the reliability of the results.

[5] The fact that downward trends show less persistence than upward trends is partly explained by GRINBLATT et al.'s finding that Mutual fund managers buy into 'winning' stocks but do not sell 'loosing' stocks. This stronger tendency to buy into upward moving securities reinforces positive market moves and thus creates additional momentum.
The tendency for upward trends to show more persistence does also hold, although less pronounced, after subtracting the mean from the return series and repeating the calculation as in table 5. Equally, replicating the calculations presented in tables 6a – 6c using de-meaned data does not substantially alter the results.

[6] This holds in particular for trends that last longer than 5 days. For 3 and 4 day trends the probability of the (positive) momentum to persist is highest at the London market.

[7] For surveys of this literature see, among others, DEBONDT and THALER (1996) and SHILLER (1998).

[8] NEELY (1997) also highlights that institutional restrictions may stop traders from moving against an existing trend.

[9] This argument was developed by DELONG, SHLEIFER, SUMMERS and WALDMANN (1989), who show that noise traders are able to generate their own space by driving up the market risk.

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