Do Positive Feedback Traders Act in Germany's Neuer Markt?

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In this paper we provide the first empirical evidence on the importance of positive feedback trading on the return behavior in Germany's Neuer Markt. Relying on the theoretical models of Shiller, Sentana, and Wadhwani, we exploit the link between index return autocorrelation and volatility to receive deeper insight into the return characteristics generated by traders adhering to positive feedback trading strategies. Our empirical evidence shows that positive feedback traders are present in Germany's Neuer Markt and induce negative return autocorrelation during periods of high volatility.

Introduction

The stock market boom of the mid-1990s and the subsequent stock price slowdown has renewed interest into the rationality (or irrationality) of portfolio decisions made by investors. While stock price movements in market segments of more traditional firms have been investigated intensively, the aggregate return behavior of high-tech stock market segments rarely is studied in the finance literature.[1] Germany's Neuer Markt was established in March 1997 to provide a platform for stocks of young, growth-oriented companies in sectors such as telecommunications, biotechnology, or multimedia. The discussion on stock price behavior in Germany's Neuer Markt is dominated by statements in the public press and mass media. To our best knowledge, no theoretically founded empirical investigation into the character-

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[1] An exception is Schwert (2002) who analyses the volatility behavior of stocks on the US Nasdaq.

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istics of stock return behavior in the Neuer Markt is currently available. In particular, there has been no empirical study on the presence of feedback trading as a possible force in determining the properties of returns on the Neuer Markt.

In contrast to the efficient market hypothesis (Fama, 1970, 1991), feedback trader models provide a theoretical rationale for the well-documented autocorrelation in high-frequency aggregate stock returns. While the behavioral finance literature provides a reasonable number of theoretical models of feedback trading (see, for example, Shiller, 1984; DeLong et al., 1990; Kirman, 1991, 1993; Campbell and Kyle, 1993; Shleifer, 2000), empirical investigations analyzing feedback trading as a source of index return autocorrelation are the exception.[2] The difficulty in empirically discriminating between feedback trading and other theoretical explanations for return autocorrelation–most prominently time-varying expected returns (Conrad and Kaul, 1988), non-synchronous trading (Lo and MacKinlay, 1990), and transaction costs (Mech, 1993)–are partially responsible for the gap in the literature.

In this paper, we exploit the link between return autocorrelation and volatility to receive deeper insight into the importance of positive feedback trading in Germany's Neuer Markt index returns for daily data covering the 1998–2002 period. The model of Shiller (1984) and Sentana and Wadhwani (1992) provides the theoretical basis of our investigation. In contrast to the hypotheses for index return autocorrelation mentioned above, the Shiller-Sentana-Wadhwani model has the testable implication that during periods of low volatility returns are positively autocorrelated and during periods of high volatility index return autocorrelation turns negative. The reversal in the sign of return autocorrelation is consistent with the presence of positive feedback traders in the stock market. The relationship between return autocorrelation and volatility is the major difference between the Shiller-Sentana-Wadhwani approach and the alternative hypotheses for index return autocorrelation. We use this specific characteristic to provide empirical evidence on the presence of positive feedback traders in Germany's Neuer Markt.

Feedback Trading and Autocorrelated Returns

The Shiller-Sentana-Wadhwani model captures the behavior of two distinct types of investors in the stock market. The first group, feedback traders or trend chasers, do not base their asset decisions on fundamental value and instead react to price changes. The second group, smart money investors, responds rationally to expected returns subject to their wealth limitation.

The relative demand for stocks by feedback traders, F_t, is modeled as:

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[2] Sentana and Wadhwani (1992) provide findings using various GARCH models on the existence of positive feedback trading in the US stock market. Koutmos (1997) reports empirical evidence from several developed stock markets, and Koutmos and Saidi (2001) investigate six emerging Asian stock markets.

$$F_t = \gamma R_{t-1}, \tag{1}$$

where R_{t-1} denotes the return in the previous period. The value of the parameter γ allows us to discriminate between the two types of feedback traders. $\gamma > 0$ refers to positive feedback traders, who buy stocks after a price rise and sell stocks after a price fall. Positive feedback trading can result from extrapolating expectations about stock prices or trend chasing. Furthermore, the use of stop loss orders or portfolio insurers can underlie positive feedback trading. Another form of positive feedback trading is the liquidation of investors' positions who are unable to meet margin calls (Shleifer, 2000). $\gamma < 0$ indicates negative feedback traders, who exhibit a contrarian investment strategy, i.e., investors buy stocks after a price fall and sell stocks after a price increase.

The proportionate demand for stocks by smart money traders, S_t, is determined by a mean-variance model:

$$S_t = (E_{t-1}R_t - \alpha)/\theta_t, \tag{2}$$

where E_{t-1} denotes the expectation operator, α the return at which the demand for shares by smart money traders is zero, and θ_t the risk premium. Smart money traders hold a higher proportion of stocks the higher $E_{t-1}R_t - \alpha$ and the smaller θ_t. The risk premium is modeled as a positive function of the conditional variance, σ_t^2, of stock prices $\theta_t = \theta(\sigma_t^2)$.

Equilibrium in the stock market requires that all stocks are held:

$$S_t + F_t = 1. \tag{3}$$

If all investors are smart money traders, $F_t = 0$, then market equilibrium, $S_t = 1$, yields Merton's (1973) capital asset pricing model:

$$E_{t-1}R_t - \alpha = \theta(\sigma_t^2). \tag{4}$$

Allowing for the existence of both groups in the stock market and substituting equation (1) and equation (2) into equation (3) yields, after rearranging and under the assumption of rational expectations $R_t = E_{t-1}R_t + \varepsilon_t$:

$$R_t = \alpha + \theta(\sigma_t^2) - \gamma\theta(\sigma_t^2)R_{t-1} + \varepsilon_t. \tag{5}$$

As can be seen from equation (5), in a market with smart money traders as well as feedback traders, the resulting return equation contains the additional term R_{t-1}, so that stock returns exhibit autocorrelation. The pattern of autocorrelation in returns depends on the type of feedback traders captured by the parameter γ, where positive (negative) feedback trading, $\gamma > 0$ $(\gamma < 0)$, implies negatively (positively) autocorrelated returns.

Relying on a linear form for $\theta(\sigma_t^2)$, equation (5) can be reformulated as:

$$R_t = \alpha + \theta(\sigma_t^2) - (\gamma_0 + \gamma_1\sigma_t^2)R_{t-1} + \varepsilon_t. \tag{6}$$

Equation (6) is crucial for our empirical investigation. First of all, imagine a constant and low risk level σ_t^2. In this case the direct impact of feedback traders on return autocorrelation is given by the sign of the parameter γ_0, where negative (positive) feedback trading $\gamma_0 < 0$ $(\gamma_0 > 0)$ results in positively (negatively) autocorrelated returns. Now suppose γ_0 is negative and γ_1 is positive. At low volatility levels Sentana and Wadhwani hypothesize that negative feedback trading dominates, which induces positive serial correlation in returns due to the relative strength of γ_0 compared to $\gamma_1\sigma_t^2$. As risk increases, the influence of $\gamma_1\sigma_t^2$ outweighs that of γ_0 and induces negatively autocorrelated stock returns due to the dominance of positive feedback traders.

Negative feedback trading is only one hypothesis that explains positive autocorrelation in daily stock returns. Other potential explanations most often proposed in the finance literature are time-varying expected returns, nonsynchronous trading, and transaction costs. The empirical evidence demonstrates that the degree of daily aggregate return autocorrelation is too large to be explained by these arguments. For example, Mech (1993), Ogden (1997), and McQueen et al. (1996) provide little empirical support that returns are serially correlated due to time-varying risk premiums. Similarly, Mech's (1993) transaction costs argument and Lo and MacKinlay's (1988, 1990) nonsychronous trading hypothesis cannot completely account for the observed autocorrelation (see, in addition, Boudoukh et al., 1994). Furthermore, in contrast to these hypotheses the Shiller-Sentana-Wadhwani approach relies on the interaction between return autocorrelation and volatility and implies that during high volatility periods return autocorrelation turns negative.

Nevertheless, we cannot ignore these hypotheses as empirically valid theoretical explanations for positively autocorrelated index returns. To answer the question "Do Positive Feedback Traders Act in Germany's Neuer Markt?" we identify periods of high volatility and investigate the specific return characteristics for these periods. Are there enough positive feedback traders during periods of high volatility to induce negative return autocorrelation and to overcompensate for the positive autocorrelation in returns due to negative feedback trading and/or due to the other possible explanations? We answer this question in the next section.

Data, Methodology, and Empirical Findings

The sample consists of daily data of the Nemax 50 and the Nemax-All-Share index for the period from January 2, 1998 to December 30, 2002. From the daily close prices, P_t, we calculate the return as the percent logarithmic difference, i.e., $R_t = (\ln P_t - \ln P_{t-1}) \cdot 100$. The daily continuously compounded returns are not annualized. In addition, the return behavior of the Nemax 50 and the Nemax-All-Share is compared with the German stock market index Dax, the S&P 500 as well as the two Nasdaq indices NSDQ 100 and NSDQCOM. These time series also cover the period from January 2, 1998 to December 30, 2002.

First, Table 1 reports the correlation coefficients between the returns of the two Neuer Markt indices, the Dax, and the three US indices. While the correlation coefficients between the two Neuer Markt indices and the Dax are about 0.70, the coefficients between the three German and the US indices range from 0.38 to 0.52. Next, Table 2 contains the mean, standard deviation, skewness, and excess kurtosis for the daily returns as descriptive statistics. Due to the selected period, it is not surprising that the averages of the daily returns are close to zero and slightly negative. The standard deviations are higher for the two Neuer Markt indices and the Nasdaq indices than for the Dax and the S&P 500. While the skewness statistics provide mixed results across the indices, the measures of excess kurtosis uniformly reject normality of the returns.

Table 1—Correlation between Different Index Returns

	Nemax 50	Nemax-All-Share	Dax	S&P 500	NSDQ 100	NSDQCOM
Nemax 50	–	0.96	0.68	0.42	0.40	0.46
Nemax-All-Share		–	0.69	0.40	0.38	0.45
Dax			–	0.52	0.41	0.45
S&P 500				–	0.83	0.85
NSDQ 100					–	0.98
NSDQCOM						–

Note: The correlation coefficients are calculated using daily close prices for the period from January 2, 1998 to December 31, 2002 and continuously compounded returns

In addition, Table 2 contains Ljung and Box's (1978) Q statistics, Q_l, with up to $l = 1, \dots, 5$ autocorrelation coefficients and variance ratio (Cochrane, 1988) test statistics, VR_l, $l = 2{,}10$ for the return time series. It should be noted that the returns of the Nemax 50 index and the Nemax-All-Share index exhibit significant autocorrelation, while the statistics for the other index returns are in the majority of cases insignificant. The NSDQ 100 returns are an exception. Interestingly, there is a drastic increase of the values of Ljung-Box Q statistics from $l = 4$ for the Nemax 50 index and the Nemax-All-Share index, which has to be considered when estimating the models.

Findings on higher moment autocorrelation are provided by the Ljung-Box Q statistics, Q_{10}^2, which are applied to the squared returns. As can be seen in Table 2, the Q_{10}^2 statistics for all indices are significant. The well-documented empirical regularities encountered in almost all high frequency financial time series hold for Germany's Neuer Markt as well. In addition, the strong positive autocorrelation in the Neuer Markt's daily index returns is contrary to other German and US index returns.

The index return autocorrelation may vary over time with the dominance of positive or negative feedback traders, which in turn should be a function of return volatility. To introduce a volatility term into the mean equation, we use the exponential GARCH (EGARCH) methodology proposed by Nelson (1991). The following equations:

Table 2—Time Series Characteristics of Index Returns

	Nemax 50	Nemax-All-Share	DAX	S&P 500	NSDQ 100	NSDQCOM
Mean	– 0.08	– 0.07	– 0.03	– 0.004	0.003	– 0.009
SD	3.03	2.65	1.83	1.35	2.81	2.30
Skew	0.11	0.05	– 0.15	0.02	0.18	0.10
	(0.10)*	(0.44)	(0.03)**	(0.76)	(0.01)***	(0.15)
Kurt	1.54	1.55	1.74	1.83	1.85	2.02
	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.03)**	(0.00)***
Q_1	14.25	20.58	0.04	0.03	4.81	0.03
	(0.00)***	(0.00)***	(0.85)	(0.86)	(0.03)**	(0.87)
Q_2	15.75	22.34	1.70	0.72	6.61	0.76
	(0.00)***	(0.00)***	(0.43)	(0.70)	(0.04)**	(0.68)
Q_3	16.01	22.38	3.41	3.58	7.22	1.31
	(0.00)***	(0.00)***	(0.33)	(0.31)	(0.07)*	(0.73)
Q_4	27.68	39.04	7.84	3.89	7.29	1.32
	(0.00)***	(0.00)***	(0.10)*	(0.42)	(0.12)	(0.86)
Q_5	27.68	40.23	8.13	4.00	7.78	1.73
	(0.00)***	(0.00)***	(0.15)	(0.55)	(0.17)	(0.88)
Q^2_{10}	200.85	235.39	727.08	205.24	219.82	299.94
	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***
VR_2	1.10	1.13	1.00	0.99	0.94	0.99
	(3.76)***	(4.53)***	(0.18)	(– 0.22)	(– 2.22)**	(– 0.18)
VR_{10}	1.37	1.50	0.95	0.83	0.77	0.92
	(4.06)***	(5.45)***	(– 0.58)	(– 1.82)*	(– 2.46)**	(– 0.91)

Note: Mean is the simple average and SD the standard deviation of the returns. Skew denotes skewness and Kurt excess kurtosis. Q_l and Q^2_l are the Ljung-Box Q (1978) statistics for the returns and the squared returns, respectively. p-values are in parentheses and l is the number of autocorrelations. VR_l are the variance ratios with N(0,1) test statistics in parentheses. *, **, *** denote significant statistics at the 10 percent, 5 percent, and 1 percent level, respectively. Daily data from 1998:1:2 to 2002:12:30 are used. The returns are continuously compounded and not annualized

$$R_t = \alpha + \theta(\sigma_t) + (\gamma_0 + \gamma_1\sigma_t)R_{t-1} + \sum_{i=2}^{5}\gamma_i R_{t-i} + \varepsilon_t\,, \tag{7}$$

$$\ln\sigma_t^2 = \beta_0 + \beta_1 g_{t-1} + \beta_2 \ln\sigma_{t-1}^2\,, \tag{8}$$

and:

$$g_t = \psi z_t + \delta\left(|z_t| - E|z_t|\right) \tag{9}$$

are jointly estimated. To take into account higher order autocorrelation in index returns we have included in the mean equation (7) autoregressive components of higher order,

$$\sum_{i=2}^{5}\gamma_i R_{t-i}\ .$$

This allows us to perform a testing down approach by starting with the unrestricted model and eliminating all statistically insignificant parameters. In equation (9), $z_t = \varepsilon_t / \sigma_t$ denotes the standardized innovation. The construction of g_t allows the conditional variance process, σ_t^2, to respond asymmetrically to increases and decreases in index returns. If $z_t > 0$, g_t is linear in z_t with slope $\psi + \delta$, and if $z_t \leq 0$, g_t is linear in z_t with slope $\psi - \delta$ (Nelson, 1991). This allows us to provide empirical evidence on the leverage effect (Black, 1976) as a theoretical justification of asymmetric stock return volatility. According to the leverage effect stock price decreases increase the debt to equity ratio, which in turn increases stock return volatility relative to stock price increases.

Many studies dealing with index returns employ the normal density function. Bollerslev and Wooldridge (1992) show that under fairly weak conditions the resulting (quasi maximum likelihood) estimates are consistent even when the conditional distribution of the residuals is non-normal. In this paper, we follow a different estimation strategy. Instead of assuming normality, we explicitly allow for tail-thickness by applying the generalized error distribution (GED) to model the conditional distribution of the residuals (Nelson, 1991). This approach is more flexible because the normal distribution (among many others) is nested in the GED and these distributions are distinguished by the tail-thickness parameter υ which has to be estimated. We use RATS 5.0 programming for the maximum likelihood estimation of parameters. Robust estimates of the covariance matrices of the parameter estimates are calculated using the BFGS algorithm.

The estimation results are summarized in Table 3. Findings for the unrestricted models (columns 2 and 4) and the restricted models (columns 3 and 5) for the Nemax 50 and the Nemax-All-Share indices are reported. For both indices the likelihood ratio statistics with five degrees of freedom are statistically insignificant at all standard levels (6.40 and 7.54, respectively), indicating that the additional parameters of the unrestricted models do not increase the log likelihood significantly. This implies that in both Neuer Markt return time series, no drift term and no risk premium term can be found. With the exception of $i = 4$ the coefficients of the autoregressive components are insignificant.

Concerning the GARCH parameters, the coefficients describing the conditional variance process are statistically significant in all cases.[3] When analyzing the estimates for ψ and δ, there is evidence of asymmetry in the dependence of the volatility from positive and negative innovations. Considering the restricted models (columns 3 and 5 in Table 3) we find that if $z_t > 0$, g_t is linear in z_t with slope $\hat{\psi} + \hat{\delta} = 1.44$ for the Nemax 50 and $\hat{\psi} + \hat{\delta} = 1.52$ for the Nemax-All-Share. If, in contrast, $z_t \leq 0$, g_t is linear in z_t with slope $\hat{\psi} - \hat{\delta} = -2.66$ for both the Nemax 50 and the Nemax-All-Share. Thus, the impact of negative innovations is larger than the impact of positive innovations. This implies that in Germany's Neuer Markt the

[3] In addition to the EGARCH(1, 1) specification we experimented with processes of higher order. The coefficients of higher order processes are statistically insignificant (results are not shown but available on request) which justifies the use of the parsimonious EGARCH(1, 1) model.

Table 3—EGARCH(1,1) Parameter Estimates

	Nemax 50		Nemax All Share	
$\hat{\alpha}$	− 0.41		− 0.54	
	(0.35)		(0.21)**	
$\hat{\theta}$	0.10		0.19	
	(0.12)		(0.10)*	
$\hat{\gamma}_0$	0.42	0.39	0.36	0.37
	(0.11)***	(0.13)***	(0.08)***	(0.10)***
$\hat{\gamma}_1$	− 0.09	− 0.09	− 0.08	− 0.08
	(0.03)***	(0.04)**	(0.03)***	(0.01)***
$\hat{\gamma}_2$	0.02		0.02	
	(0.008)**		(0.02)	
$\hat{\gamma}_3$	− 0.008		0.01	
	(0.02)		(0.02)	
$\hat{\gamma}_4$	0.08	0.08	0.10	0.10
	(0.02)***	(0.02)***	(0.02)***	(0.02)***
$\hat{\gamma}_5$	0.008		0.03	
	(0.02)		(0.02)	
$\hat{\beta}_0$	0.19	0.15	0.14	0.11
	(0.12)*	(0.07)**	(0.04)***	(0.05)**
$\hat{\beta}_1$	0.13	0.13	0.13	0.13
	(0.01)***	(0.01)***	(0.01)***	(0.01)***
$\hat{\beta}_2$	0.91	0.93	0.92	0.94
	(0.06)***	(0.03)***	(0.02)***	(0.03)***
$\hat{\psi}$	− 0.75	− 0.61	− 0.68	− 0.57
	(0.22)***	(0.16)***	(0.16)***	(0.16)***
$\hat{\delta}$	2.14	2.05	2.18	2.09
	(0.27)***	(0.26)***	(0.19)***	(0.20)***
$\hat{\upsilon}$	1.45	1.46	1.50	1.50
	(0.07)***	(0.07)***	(0.07)***	(0.09)***
Q_1	0.13	0.02	0.17	0.00003
	(0.72)	(0.89)	(0.68)	(0.99)
Q_2	1.82	2.97	1.95	2.93
	(0.40)	(0.23)	(0.38)	(0.23)
Q_3	1.82	3.21	1.96	2.94
	(0.61)	(0.36)	(0.58)	(0.40)
Q_4	2.06	3.39	2.01	2.94
	(0.72)	(0.50)	(0.73)	(0.57)
Q_5	2.12	3.43	2.01	3.35
	(0.83)	(0.63)	(0.85)	(0.65)
Q^2_{10}	6.20	6.23	12.95	14.37
	(0.80)	(0.80)	(0.23)	(0.16)

The estimated parameters rely on the model

$$R_t = \alpha + \theta(\sigma_t) + (\gamma_0 + \gamma_1\sigma_t)R_{t-1} + \sum_{i=2}^{5}\gamma_i R_{t-i} + \varepsilon_t ,$$

$$\ln\sigma_t^2 = \beta_0 + \beta_1 g_{t-1} + \beta_2 \ln\sigma_{t-1}^2 \text{ and}$$

$$g_t = \psi z_t + \delta(|z_t| - E|z_t|) .$$

The equations are jointly estimated via maximum likelihood. The estimation is carried out under the assumption of conditional GED distribution. Standard errors in parentheses are based on robust estimates of the covariance matrices of the parameter estimates. Q_l and Q_l^2 are the Ljung-Box Q (1978) statistics for the residuals and the squared residuals, respectively, with p-values in parentheses. l is the number of autocorrelations. *, **, *** denote statistical significance at the 10 percent, 5 percent, and 1 percent level, respectively. Daily data from 1998:1:2 to 2002:12:30 are used volatility is higher in periods of market decline compared to bullish market periods, which can be theoretically justified by the leverage effect.

The estimates of the β_2 coefficients reveal a high degree of shock persistence in volatility. Furthermore, the estimated model generates thick tails with both a randomly changing conditional variance and a thick-tailed conditional distribution for the standardized errors. According to the values of $\hat{\upsilon}$ the distribution of $\hat{\varepsilon}_t$ is significantly thicker-tailed than the normal $(\upsilon = 2)$. Table 3 also reports Ljung-Box Q statistics relating to the standardized residuals and to the squared standardized residuals of the estimated models, thereby testing for serial correlation and autoregressive conditional heteroskedasticity. The statistics indicate that the EGARCH models are able to capture autocorrelation and conditional heteroskedasticity of Nemax 50 and Nemax All-Share index returns.

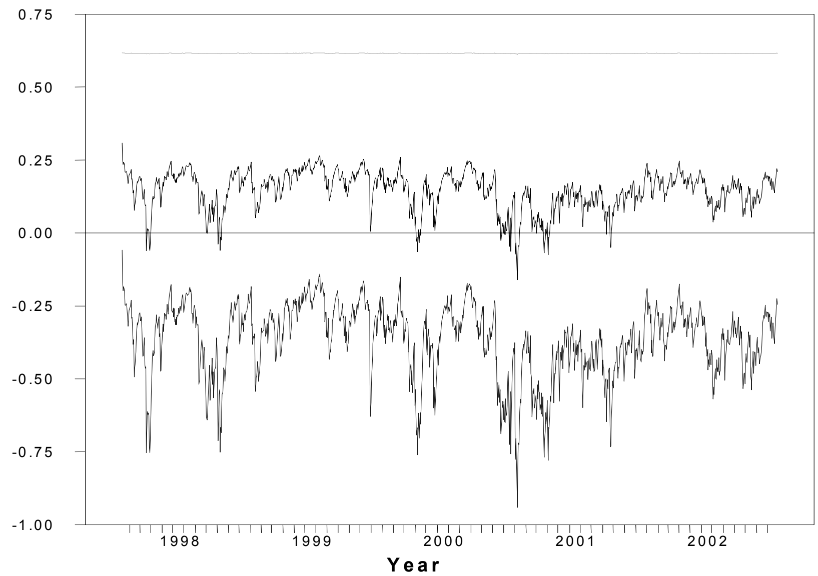
We now turn to the findings of the crucial parameter estimates $\hat{\gamma}_0$ and $\hat{\gamma}_1$ to answer the question about the existence of positive feedback traders in the Neuer Markt. Consistent with our theoretical suggestions for both indices, the $\hat{\gamma}_0$ coefficients are statistically significant positive, while the parameters $\hat{\gamma}_1$ are significant negative. The estimated values $\hat{\gamma}_0$ and $\hat{\gamma}_1$ imply that for conditional standard deviations up to $\sigma_t = 4.33$ for the Nemax 50 index and $\sigma_t = 4.63$ for the Nemax-All-Share index, returns exhibit positive autocorrelation and for values above these limits reveal negative return autocorrelation.

To provide a graphical representation of the conditional autocorrelation coefficient, ρ_t, we calculate ρ_t according to equation (7) as $\rho_t = \hat{\gamma}_0 + \hat{\gamma}_1 \cdot \sigma_t$ for the Nemax 50 index and the Nemax-All-Share index returns. Of course, the implied autocorrelation coefficient may occasionally exceed one in magnitude so that the assumption of return stationarity cannot be maintained any longer. Thus, it is important to provide information about the distribution of ρ_t. This is done in two steps. First, we analyze the distribution of the parameters γ_0 and γ_1 by means of a bootstrap and compute their 95 percent confidence band.[4] The upper and the lower values of either band are then used to constitute the 95 percent confidence interval of the conditional autocorrelation coefficient. The time series of ρ_t together with a 95 percent confidence band are plotted in Figure 1 for the Nemax 50 index returns and in Figure 2 for the Nemax-All-Share index returns.

As can be seen from the confidence intervals in Figures 1 and 2, the autocorrelation coefficients do not exceed the critical magnitude of one at the 95 percent confidence level indicating that the estimates of γ_0 and γ_1 are reliable. Due to the fact that the 97.5 percentile of γ_1 is close to zero in either case, the upper margin of the confidence interval is almost flat. In contrast, the 2.5 percentile of γ_1 is greater than the estimated $\hat{\gamma}_1$ in absolute value, thereby amplifying changes in the conditional autocorrelation.

[4] The bootstrap algorithm is available from the authors on request.

Figure 1—Conditional First Order Autocorrelation of Nemax 50, Daily Data 1998-2002

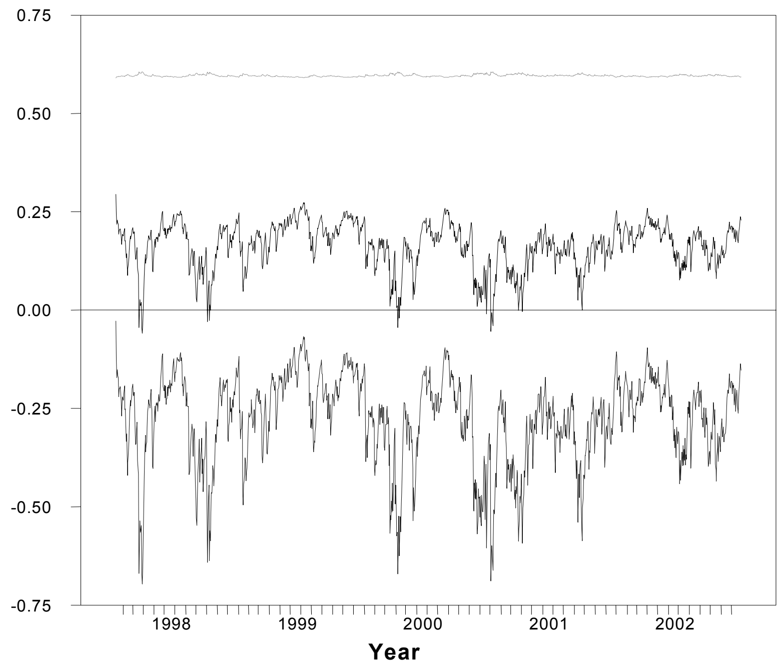


In general, the time series of ρ_t remains in the range between zero and 0.25, indicating positive return autocorrelation. During periods of high volatility, however, there are enough positive feedback traders acting in the Neuer Markt to generate negative autocorrelated returns. This is the case even though other factors such as time-varying expected returns, nonsynchronous trading, and transaction costs tend to induce positive index return autocorrelation. Our findings for Germany's Neuer Markt are broadly consistent with the empirical evidence in Sentana and Wadhwani (1992), Koutmos (1997), and Koutmos and Saidi (2001) for other developed as well as emerging stock markets.

Conclusion

In this paper we provide the first empirical evidence on the importance of positive feedback trading for the return behavior in Germany's stock market segment for stocks of young, growth-oriented firms, the so-called Neuer Markt. Relying on the theoretical models of Shiller (1984) and Sentana and Wadhwani (1992), we exploit the link between index return autocorrelation and volatility to receive deeper insight into the return characteristics induced by traders adhering to positive feedback trading strategies. Germany's Neuer Markt is extremely volatile and, therefore, provides an interesting platform for an investigation of feedback trading strategies.

Figure 2—Conditional First Order Autocorrelation of Nemax-All-Share, Daily Data 1998-2002



Using Nelson's (1991) exponential GARCH model for daily data from January 2, 1998 to December 30, 2002, it is possible for the conditional variance to respond asymmetrically to positive and negative innovations. The findings provide support for the existence of a leverage effect, which implies that in Germany's Neuer Markt volatility is higher in bearish periods compared to bullish periods. More important, our empirical evidence shows that during periods of high volatility positive feedback traders are present in Germany's Neuer Markt and induce negative return autocorrelation.

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