The Influence of Positive Feedback Trading on Return Autocorrelation: Evidence for the German Stock Market

Abstract:

In this paper we provide empirical findings on the significance of positive feedback trading for the return behavior in the German stock market. Relying on the Shiller-Sentana-Wadhwani model, we use the link between index return auto-correlation and volatility to obtain a better understanding into the return characteristics generated by traders adhering to positive feedback trading strategies. Our empirical evidence shows that in the German stock market a significant proportion of investors are positive feedback traders and that this positive feedback trading seems to be responsible for the observed negative return autocorrelation during periods of high volatility.

JEL Classification: G14, C22

Keywords: Return Autocorrelation, Positive and Negative Feedback Trading, German Stock Market

1. Introduction

There can be no doubt that some investors try to discover trends in past stock prices and base their portfolio decisions on the expectation that these trends will persist. In the behavioral finance literature this type of investors is usually called a feedback trader. Positive feedback traders buy stocks in a rising market and sell stocks in a falling market, while negative feedback traders adhere to a “buy low, sell high” investment strategy. One of the consequences of the existence of a sufficiently large number of feedback traders in the stock market is the autocorrelation of returns and, hence, the partial predictability of aggregate stock returns. On the one hand, the behavioral finance literature provides a fair amount of theoretical models of feedback trading, and the experimental findings, as well as, the survey evidence overwhelmingly support the existence of positive feedback traders.[1] On the other hand, the empirical evidence is mixed with respect to the presence of feedback traders in stock markets and the resulting consequences for return behavior.

For example, Shefrin and Statman (1985) and Odean (1998) provide evidence in favor of the disposition effect, i. e. investors are reluctant to realize losses and they sell winners too early, which contradicts the positive feedback hypothesis. Lakonishok, Shleifer, and Vishny (1992) investigate positive feedback strategies taken by institutional investors and find, with the exception of small stocks, no evidence of

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[1] Theoretical models on feedback trading can be found in Shiller (1984), DeLong, Shleifer, Summers, and Waldmann (1990), Cutler, Poterba, and Summers (1990), Kirman (1993), Campbell and Kyle (1993), and Shleifer (2000). Kroll, Levy, and Rapoport (1988), Shiller (1988), De Bondt (1993), and Bange (2000) among others provide experimental and survey evidence.

positive feedback trading in pension funds. Whereas, the time series evidence contained in Sentana and Wadhwani (1992), Campbell and Kyle (1993), Koutmos (1997), and Koutmos and Said (2001) supports to a large extent the notion of positive feedback trading in developed, as well as, emerging stock markets.

The aspects outlined above shows that empirical studies analyzing feedback trading provide inconclusive evidence and that there are only a few empirical studies in the existing literature. Lack of data, as well as, the difficulty to discriminate empirically between feedback trading and other theoretical explanations for return autocorrelation – most prominently non-synchronous trading (Lo and MacKinlay, 1990), time-varying expected returns (Conrad and Kaul, 1988, 1989) and transaction costs (Mech, 1993) – are responsible for the gap in the literature to find sufficient evidence on the contribution of feedback trading for autocorrelated returns.

In this paper we use the link between return autocorrelation and volatility to better understand the significance of positive feedback trading in Germany's stock market by analyzing daily data of the C-Dax, the Dax, and the Nemax50 index over the 1998 – 2001 period. The small number of empirical studies on the impact of feedback trading on return autocorrelation and the concentration in the empirical finance literature on the US stock market motivates our selection of the German stock market. Providing empirical evidence for German stock price indices reduces the data snooping bias and allows to compare our findings with the previous literature.

The theoretical point of departure is the feedback trader model put forward by Shiller (1984) and Sentana and Wadhwani (1992). Nelson's (1991) exponential GARCH model and an event study focusing on the September 11, 2001, crash provide the methodological basis. There has been no empirical study on the presence of feedback trading as one of the possible forces determining the properties of returns in Germany's stock market. We are interested in the question of whether positive feedback traders are present in Germany's stock market and, if so, what it implies for return behavior.

The rest of the paper is organized as follows: Section 2 outlines the feedback trader model. The discussion of the testing strategies and the empirical findings are presented in Section 3. Section 4 provides the conclusion.

2. Feedback Trading and Autocorrelated Returns

The Shiller-Sentana-Wadhwani model (Shiller, 1984; Sentana and Wadhwani, 1992) captures the behavior of two distinct types of investors in the stock market. Feedback traders or trend chasers as a group do not base their asset decisions on fundamental value and instead react to price changes. Their demand for stocks is based on the history of past returns rather than expected fundamentals. The second group, smart money investors, responds rationally to expected returns subject to their wealth limitation. The presence of both groups in the stock market and their specific behavior provides the theoretical rational for serially correlated stock returns and the importance of volatility for the return autocorrelation characteristics.

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

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

where R_{t-1} denotes the return in the previous period. The value of the parameter γ permits the differentation between the two types of feedback traders. $\gamma > 0$ refers to the case of positive feedback traders, who buy stocks after a price rise and sell stocks after a price fall. Buying in a rising market and selling in a falling market can result from extrapolating expectations about stock prices or trend chasing. Furthermore, portfolio insurance is an example of a positive feedback trading strategy. This strategy implies that in a rising market a higher proportion of wealth is investigated in stocks, which generates stock price increases. In a falling market, a lower proportion of wealth is investigated in stocks by the portfolio insurance strategy, which results in stock sales and stock price decreases. Another form of positive feedback trading is the use of stop loss orders, which prescribe selling after a certain level of losses regardless of future prospects. Moreover, the effects of the liquidation of investors' positions who are unable to meet margin calls are comparable to the impacts of a positive feedback trading strategy.

$\gamma < 0$ indicates the case of negative feedback trading. Unlike a positive feedback trader, the negative feedback trader exhibits a "buy low, sell high" strategy, i. e. selling stocks after price increases and buying stocks after price declines. Negative feedback trading can result from profit taking as markets rise or from investment strategies that target a constant share of wealth in different assets.

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

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

where E_{t-1} denotes the expectation operator and α the return on a risk free asset. In this model smart money traders hold a higher proportion of stocks, the higher the expected excess return, $E_{t-1}R_t - \alpha$, and the smaller the riskiness of stocks, μ_t. The risk measure is modelled as a positive function of the conditional variance, σ_t^2, of stock prices $\mu_t = \mu(\sigma_t^2)$, where the first derivation is positive reflecting risk averse investing behavior.

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:

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

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

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

As can be seen from equation (5) in a market with smart money investors, 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 trader captured by the parameter γ, where positive (negative) feedback trading, $\gamma > 0$ $(\gamma < 0)$, implies negatively (positively) autocorrelated returns.

Furthermore, the extent to which returns exhibit autocorrelation varies with the level of return volatility, $\mu(\sigma_t^2)$. For example, if there is an increase in volatility, smart money readers reduce the demand for stocks (see equation (2)), which allows feedback traders to have a greater impact on the stock price. Consequently, a larger discrepancy between the current stock price and its fundamental value results. This is due to the larger proportion of stocks demanded by feedback traders so that stock returns exhibit stronger autocorrelation.

The pattern of autocorrelation is determined by the type of feedback trader and the extent of volatility, which becomes obvious when relying on a linear form for $\mu(\sigma_t^2)$ in equation (5):

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

Equation (6) is crucial for our empirical investigation. First of all, at a constant risk level, σ_t^2, the direct impact of feedback traders 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. 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 larger influence of $\gamma_1 \sigma_t^2$ compared to γ_0 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 often proposed in the finance literature are non-synchronous trading, time-varying expected returns, and transaction costs. The first, and most prominent, explanation states that index return autocorrelation results due to non-synchronous trade price observations of the stocks in an index. Stock prices are computed at fixed points in time, for example, at the close of each trading day. Generally, the last price observed for each share prior to point *t* is used to compile the index at time *t*. Since trading occurs at discrete points in time for some stocks the last trade may have occurred at an earlier point in time, while for other stocks the last trade may have occurred just prior to time *t*. Consequently, the value of the index reflects a mixture of stale, as well as, contemporaneous trade prices. The positive autocorrelation in index returns is induced because traded and non-traded shares are grouped into an index and, hence, some of the returns for the interval $t-1$ to t reflect information arriving in the previous interval $t-2$ to $t-1$ (Lo and MacKinlay, 1990).

The second explanation postulates that the expected returns on stocks share a common, positively autocorrelated process. Autocorrelation in expected returns is driven by serially correlated risk premiums that in turn induces autocorrelation in raw returns of the individual and index returns. Time-varying risk premiums can be explained by intertemporal asset pricing models, such as conditional versions of the arbitrage pricing theory or the consumption based asset pricing model. Variation in risk factors induce variation in short-horizon risk premiums (Conrad and Kaul, 1988, 1989). According to the third explanation investors do not trade on new information if gains due trading are lower than information and transaction costs. Costs of processing information and direct trading costs may inhibit trading and therefore, delay the transmission of new information into stock prices. If the index contains stocks that immediately reflect new information, as well as, stocks that do not, then index returns exhibit positive autocorrelation (Mech, 1993).

Available empirical evidence demonstrates that the degree of daily aggregate return autocorrelation is too large to be explainable by the arguments mentioned above. For example, Mech (1993), Ogden (1997), McQueen, Pinegar, and Thorley (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 (1990) non-synchronous trading hypothesis cannot completely account for the observed autocorrelations (see also, Boudoukh, Richardson, and Whitelaw, 1994).

Nevertheless, we cannot entirely ignore these hypotheses as empirically valid theoretical explanations for positively autocorrelated index returns although none of these approaches explicitly relies on the relationship between return autocorrelation and volatility. Our proposed method to answer the question of whether positive feedback traders act in Germany's stock market is to 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 generate negative return autocorrelation and to overcompensate 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.

3. Data, Methodology, and Empirical Findings

The time series used for our empirical investigation consist of daily data of the C-Dax, the Dax, and the Nemax50 index for the period from January 1, 1998 to November 1, 2001, which amounts to about 1000 observations. The C-Dax covers approximately 675 shares and is therefore a very broad index. The Dax contains 30 German blue chips and reflects stock price development in the market segment belonging to the more traditional firms. The Nemax50 contains the largest high-tech companies in the Neuer Markt. The utilization of these indices enables us to provide a broad picture of the question under scrutiny and the unique sample length allows a direct comparison of the empirical findings. From the daily close prices, we calculate the index return as the percentage of the logarithmic difference, i. e. $R_t = (\ln P_t - \ln P_{t-1}) \cdot 100$, where P_t is the index at time t.

To provide preliminary evidence on the link between volatility and autocorrelation of index returns, we undertake the following experiment. Few economists would disagree that stock market volatility dramatically increased during the days after the terrorist acts in the U.S. on September 11, 2001. This stock market crash enables us to assess the effects of volatility on the autocorrelation properties of stock returns without having to model a measure of volatility. Therefore, we estimate the following autoregression:

$$R_t = \alpha + (\gamma_0 + \gamma_1 Crash_t) R_{t-1} + \varepsilon_t, \tag{7}$$

where the dummy variable $Crash_t$ is equal to one during the crash week (September 11 to 14), during the five trading days after the crash (September 11 to 18), during the September 19 to 25 period, and equal to zero otherwise. According to the theoretical discussion in Section 2, we expect a statistically significant negative parameter γ_1 at least for the two periods directly after the September 11 crash due to positive feedback trading strategies. With a reduction in volatility the negative autocorrelation in stock returns possibly vanishes during the third period resulting in no, or positive autocorrelated returns.

Table 1 about here

Table 1 contains the results of our experiment. With only one exception, the estimated parameters of the crash dummies are for the first two periods (September 11 to 14 and September 11 to 18) statistically significant negative (at least) at the 5 % level. In contrast, all estimated parameters γ_1 for the September 19 to 25 period are statistically insignificant from zero. These results suggest that there are enough positive feedback traders in the German stock market generating negative serially correlated returns during periods of high volatility. During the period of lower volatility, after most of the impact of the terrorist attacks vanished, C-Dax, Dax, and Nemax50 returns do not show statistically significant negative first order return autocorrelation.

Clearly, the simple dummy analysis cannot be fully convincing. The reported negative autocorrelation is based only on a few observations, the selection of the dummy periods is arbitrary, and there is no explicit measure of volatility. These three arguments indicate a more rigorous analysis. Table 2 provides an overview of the time series characteristics of the C-Dax, Dax, and Nemax50 indices by reporting mean, variance, skewness, and kurtosis for the daily returns. The times series of all index returns are driftless and the unconditional variance for the Nemax50 index returns is significantly higher than the variances for the C-Dax and the Dax. Like almost all high frequency financial data, normality of the return distribution is rejected by the measures of skewness and kurtosis. An inspection of Table 2 suggests that the C-Dax, Dax, and Nemax50 returns have to be modelled as heteroskedastic and/or fat-tailed.

Table 2 about here

As is shown in Section 2 of the paper, 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) where equation (6) is jointly estimated with:

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

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

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 $z_t > 0$, then g_t is linear in z_t with slope $\psi + \delta$, and if $z_t \le 0$, then g_t is linear in z_t with slope $\psi - \delta$. 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 declines 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. However, in this case the parameter estimates are not asymptotically efficient because the standardized residuals appear to be leptokurtic. To prevent parameter estimates from being influenced by outliers with low probability we use the generalized error distribution.

The estimation results are summarized in Table 3. The coefficients describing the conditional variance process are statistically significant in all cases.[2] When looking at the estimates for ψ and δ there is evidence of asymmetry in the dependence of the volatility from negative and positive innovations. The impact of negative innovations is at least twice as large as the impact of positive innovations. This implies that in the index returns under consideration the volatility is higher in periods of market decline than in market upturns, 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 the $\hat{\varepsilon}_t$ is significantly thicker-tailed than the normal distribution.

Table 3 about here

We now turn to the crucial findings of the parameter estimates $\hat{\gamma}_0$ and $\hat{\gamma}_1$ to answer the question about the existence of positive feedback traders in the three German stock market segments. The results are consistent with our theoretical suggestions because all $\hat{\gamma}_0$ coefficients are statistically significant negative and the $\hat{\gamma}_1$

[2] 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.

parameters are significant positive. During periods of high volatility there is enough positive feedback trading in the German stock market to produce negative first order autocorrelated returns, even though other factors tend to generate positive autocorrelation. These findings are broadly consistent with the empirical evidence in Sentana and Wadhwani (1992), Koutmos (1997), and Koutmos and Said (2001) for other developed, as well as, emerging stock markets.

So far, the empirical results meet the necessary condition that the estimates for γ_0 and γ_1 have the expected signs. But according to equation (6), stock index returns only exhibit negative autocorrelation if the magnitude of a negative γ_1 is sufficiently high to compensate for a positive γ_0, given conditional return volatilities. Therefore, we assess the empirical relevance of positive feedback trading by calculating the autocorrelation coefficient, $\hat{\rho}_t = \hat{\gamma}_0 + \hat{\gamma}_1 \hat{\sigma}_t^2$, for the estimated minimum, mean, and maximum conditional volatility. The results are reported in Table 4.

Table 4 about here

The calculated values $\hat{\rho}_{min}$, $\hat{\rho}_{mean}$, and $\hat{\rho}_{max}$ indicate that positive feedback trading is not a phenomenon of a few trading days with peaking volatility, but can be found at (fairly low) mean volatility levels. With increasing volatility positive feedback traders have an even greater influence on the index returns inducing negative return autocorrelation which confirms the theory suggested above.

4. Conclusion

In this paper we provide empirical evidence on the importance of positive feedback trading for the return behavior in different German stock market segments. Relying on the theoretical models put forward by Shiller (1984) and Sentana and Wadhwani (1992) we use the link between index return autocorrelation and volatility to better understand the return characteristics generated by traders adhering to positive feedback trading strategies. Germany's C-Dax, Dax, and Nemax50 indices for the period from January 1, 1998 to November 1, 2001, represent different stock market segments, thereby providing an interesting and broad platform for an analysis of feedback trading strategies.

First, we provide empirical evidence relying on the stock market crash due to the terrorist acts in the U.S. on September 11, 2001. Few economists will disagree that volatility had enormously increased in the days after the stock price crash, which lead directly to the question of the autocorrelation properties in returns during this turbulent period. Our simple dummy variable approach exhibits empirical results that are consistent with the theory regarding the relationship between volatility and autocorrelation in index returns. Whereas index returns show shortly after the crash strong negative autocorrelation indicating the existence of positive feedback traders, the negative serial correlation in returns vanishes the week after the crash when volatility has decreased.

The application of Nelson's (1991) exponential GARCH model as a more sophisticated approach relies on an explicit volatility measure and allows the conditional variance to respond asymmetrically to positive and negative innovations. Our findings provide strong support for the existence of a leverage effect. This implies that in Germany’s C-Dax, Dax, and Nemax50 index volatility is higher in bearish periods compared to bullish periods. More importantly and consistent with the empirical results of the event study of the September 11 crash, our empirical evidence shows that positive feedback traders are present in these stock market segments and generate negative return autocorrelation even at mean levels of return volatility.

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Table 1: September 11 Crash and Autocorrelation in Stock Returns

Index	Dummy Period	$\hat{\alpha}$	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\overline{R}^2$
C-Dax	September 11 to 14	– 0.002 (0.05)	0.03 (0.06)	– 0.28* (2.82)	0.003
	September 11 to 18	– 0.002 (0.04)	0.02 (0.06)	– 0.25* (2.69)	0.003
	September 19 to 25	0.001 (0.02)	0.01 (0.25)	0.14 (0.51)	0.001
Dax	September 11 to 14	0.002 (0.04)	0.003 (0.06)	– 0.31* (2.38)	0.004
	September 11 to 18	0.003 (0.05)	0.002 (0.06)	– 0.28* (2.37)	0.004
	September 19 to 25	0.01 (0.13)	– 0.02 (0.42)	0.19 (0.72)	0.001
Nemax50	September 11 to 14	0.001 (0.01)	0.14* (3.41)	– 0.28* (2.73)	0.02
	September 11 to 18	0.001 (0.01)	0.14* (3.39)	– 0.23 (1.89)	0.02
	September 19 to 25	0.003 (0.03)	– 0.13* (3.42)	– 0.07 (0.16)	0.02

The estimated parameters rely on the model $R_t = \alpha + (\gamma_0 + \gamma_1 Crash_t) R_{t-1} + \varepsilon_t$. $\overline{R}^2$ denotes the adjusted coefficient of determination. *t*-statistics in parentheses are based on heteroskedastic-consistent standard errors. * denotes statistical significance (at least) at the 5 % level. Daily data from 1998:1:2 to 2001:11:1 (1000 observations) are used.

Table 2: Time Series Characteristics of Index Returns

	C-Dax	Dax	Nemax50
Mean	0.002 (0.96)	0.008 (0.88)	0.004 (0.96)
Variance	2.09	2.81	7.48
Skewness	– 0.51 (0.00)	– 0.50 (0.00)	– 0.06 (0.00)
Kurtosis	6.90 (0.00)	5.10 (0.00)	5.32 (0.00)

Index returns are calculated as $R_t = (\ln P_t - \ln P_{t-1}) \cdot 100$, where P_t is the index at time t. P-values are in parantheses. Daily data from 1998:1:2 to 2001:11:1 (1000 observations) are used.

Table 3: EGARCH(1,1) Parameter Estimates

	C-Dax	Dax	Nemax50
$\hat{\alpha}$	0.002 (0.02)	– 0.05 (0.83)	– 0.23 (0.38)
$\hat{\mu}$	0.02 (0.15)	0.06 (0.70)	0.10 (0.40)
$\hat{\gamma}_0$	– 0.15 (4.35)*	– 0.12 (5.27)*	– 0.45 (4.00)*
$\hat{\gamma}_1$	0.09 (4.43)*	0.08 (5.80)*	0.10 (2.74)*
$\hat{\beta}_0$	0.03 (2.63)*	0.04 (2.92)*	0.18 (3.03)*
$\hat{\beta}_1$	0.11 (13.94)*	0.10 (13.27)*	0.14 (14.84)*
$\hat{\beta}_2$	0.94 (53.43)*	0.95 (63.35)*	0.90 (28.50)*
$\hat{\psi}$	– 1.00 (4.56)*	– 0.93 (4.37)*	– 0.78 (3.86)*
$\hat{\delta}$	1.51 (9.31)*	1.46 (9.65)*	2.30 (12.48)*
$\hat{\upsilon}$	1.59 (14.13)*	1.55 (15.73)*	1.52 (16.34)*

The estimated parameters rely on the equations (6), (8), and (9), that are jointly estimated via maximum likelihood. *t*-statistics are in parentheses and * denotes statistical significance (at least) at the 5 % level. Daily data from 1998:1:2 to 2001:11:1 (1000 observations) are used.

Table 4: Volatility and Return Autocorrelation

	C-Dax	Dax	Nemax50
$\hat{\sigma}^2_{\text{min}}$	0.65	0.86	0.93
$\hat{\rho}_{\text{min}}$	0.09	0.05	0.36
$\hat{\sigma}^2_{\text{mean}}$	2.04	2.73	7.37
$\hat{\rho}_{\text{mean}}$	– 0.03	– 0.10	– 0.29
$\hat{\sigma}^2_{\text{max}}$	14.14	17.41	30.36
$\hat{\rho}_{\text{max}}$	– 1.12	– 1.27	– 2.59

The autocorrelation coefficients are calculated as $\hat{\rho}_{\text{t}} = \hat{\gamma}_0 + \hat{\gamma}_1 \hat{\sigma}^2_{\text{t}}$.