INVESTOR HETEROGENEITY AND STOCK RETURN DYNAMICS

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Abstract

This paper extends the dynamic (conditional) Capital Asset Pricing Model (CAPM) to incorporate the impact of three types of markets participants namely, rational risk averse investors, positive feedback, or, momentum traders and negative feedback, or, contrarian traders on the prices of risky securities. The demand for risky assets on the part of rational risk averse investors is governed by risk/reward considerations along the lines of the CAPM. Positive feedback traders are essentially trend chasers, i.e., they buy risky assets when prices move up and they sell them when prices move down. This could be the result of irrationality, lack of information, or, portfolio insurance strategies that manifest themselves as momentum, or, positive feedback trading. Negative feedback traders follow contrarian trading strategies in an attempt to exploit trend chasers, i.e., they buy when prices move down and they sell when the prices move up. The interaction of the three types of investors leads to a complex time varying autocorrelation pattern for stock returns. There is evidence of both positive and negative feedback trading in small and medium capitalization portfolios. There is no evidence of either positive or, negative feedback trading in either large capitalization portfolios or the market portfolio. The actions of positive feedback traders increases covariant risk and the deviation of prices from equilibrium values.

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I. Introduction

Recent research suggests that the Efficient Markets Hypothesis (EMH) coupled with equilibrium asset pricing models of the CAPM variety fail to explain the dynamics of asset prices. The failure has been attributed to many factors. Some researchers argue that the prices of financial assets are influenced by social norms, fashions or, fads. Consequently, asset returns exhibit volatility beyond the level that is consistent with fundamentals. Using survey evidence Shiller (1989) finds that during the crash of 1987 the single most important news item cited by investors was not related to fundamentals but to the 200-point drop of the Dow at the opening. The response from Japanese investors was similar. These responses suggest that, at times, price dynamics can be influenced by investor psychology. In a similar vain, Cutler, Poterba and Summers (1991) suggest that asset market volatility is due primarily to the interaction of different types of investors some of whom may not trade on the basis of publicly available information but on the basis of noise. According to Black (1986), it is not uncommon for investors to trade on noise as if it were information. In this case asset prices will reflect the information of well informed investors as well as the actions of investors who trade on noise. As a group noise traders are expected to lose money whereas, information traders will make money.[1] The presence of noise makes markets more liquid and more risky. Due to higher risk, informed investors do not take positions to fully eliminate the impact of noise traders. Shleifer and Summers (1990) suggest two main types of risk facing arbitrageurs in their attempts to exploit opportunities arising from noise trading namely, i) fundamental risk and ii) resale price risk. The first type of risk is due to the possibility that news about fundamentals i.e., dividends and/or earnings are better than expected. The second type of risk assumes that

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arbitrageurs have finite horizons because of a need to borrow or because of being subject to frequent performance evaluations.

Noise trading can take on many different forms. It may be liquidity trading, trading on the basis of popular models or, technical trading. Noise trading can be destabilizing only if there is a high degree of correlation among noise trading strategies. This can happen if for example, noise traders exhibit herd-like behavior. The popular belief is that institutional investors destabilize prices by herding. According to Lakonishok, Shleifer and Vishy (1992), this may happen because institutions infer information from each other's trades, watch the same indicators and finally, they are evaluated against each other.

Another, probably more destabilizing, form of noise trading is positive feedback trading. Positive feedback traders are essentially trend chasers, i.e., they buy risky assets when prices move up and they sell them when prices move down. This could be the result of extrapolative expectations, the use of stop-loss orders, irrationality, lack of information, or, portfolio insurance strategies that manifest themselves as feedback trading. Feedback trading strategies can have a dramatic effect on the prices of risky assets. If a substantial number of investors follow such strategies then the market can experience runaway prices or, devastating crashes. At a very minimum, price movements are exacerbated. A far worse scenario is one in which rational arbitrageurs reinforce positive feedback trading by jumping on the bandwagon (see DeLong, Shleifer, Summers and Waldmann 1990).

Lakonishok, Shleifer and Vishy (1992) test for both herding and positive feedback in the trading strategies of a large sample of institutional investors. They find that for small stocks there is evidence of herding and somewhat stronger evidence of positive feedback trading. The same does not hold for larger stocks however. This is in accordance with Black's (1986) assertion that noise trading and therefore misspricing, is likely to be more prevalent among small stocks.

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Most studies dealing with feedback trading take a longer term view and do not, as a rule, utilize any equilibrium asset pricing model. For example, Lakonishok, Shleifer and Vishny (1992) test for positive feedback and herding trading strategies in quarterly return data. By the authors' admission this leaves open the possibility that feedback traders destabilize either aggregate stock prices or, the prices of individual assets on a day-to-day or week-to-week basis. Studies dealing with day-to-day feedback trading are very few and they concentrate exclusively on the market index. For example, Sentana and Wadhwani (1992) use a conditional Capital Asset Pricing Model (CAPM) that assumes two types of economic agents: risk averse expected utility optimizing agents and positive feedback traders i.e., agents who buy (sell) after prices advances (declines). Using daily returns index returns for the United States stock market the authors find evidence consistent with the presence of positive feedback trading on the part of some investors. Specifically, as volatility increases feedback traders have a greater influence on price and the first order return autocorrelation becomes negative. Similar findings are reported in Koutmos (1997) for several international index returns. Focusing on the market index however, can be misleading because it is possible for feedback trading to be significant in individual stocks or, portfolios and insignificant in the market index. This is a serious limitation in light of Black's (1986) hypothesis and the findings of Lakonishok, Shleifer and Vishny (1992) that positive feedback trading is more pronounced in small stocks. Another limitation is the inability to test for the presence of negative feedback trading (buying when prices move down and selling when prices move up). Such behavior is likely to induce price stability as it counters the impact of positive feedback trading.

This paper addresses the limitations of earlier studies on feedback trading by introducing a generalized feedback trading model. Specifically, it extends the Sentana and Wadhwani (1992) model in two important ways. First, it incorporates the actions of three heterogeneous groups of investors: i) risk averse expected utility maximizers (group A), ii) positive feedback traders (group B) and iii) negative feedback traders (group C). The demand function for risky assets for group A is

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governed by risk/expected return considerations. If they perceive the future rewards to be greater than those justified on the basis of risk they increase their demand for risky assets and vice versa. Positive feedback traders (group B) are essentially trend chasers, i.e., they buy risky assets when prices move up and they sell them when prices move down. Negative feedback traders (group C) attempt to exploit group B by buying low (i.e., during markets declines) and selling high (i.e., during market advances). They are however risk averse in the sense that their willingness to exploit opportunities created by group B is tempered by the amount of risk they are exposed to. The second extension, perhaps more importantly, is the generalization of the model so that it can incorporate the interaction of the three groups at the aggregate (market) level as well as the individual asset level.

The findings are rather interesting. First, there is a positive conditional risk premium at both the market and the individual asset level. Second, there is evidence of both positive and negative feedback trading in small and medium capitalization stocks. Third, there is not evidence of either positive or, negative feedback trading in large capitalization stocks. Finally, the actions of feedback traders (positive and negative) are not significant at the market level.

The rest of this paper is organized as follows. Section II describes the model, section III describes the data used and discusses the empirical findings and finally, section IV offers a summary and conclusion.

II. Conditional CAPM with Feedback Trading

The Capital Asset Pricing Model (CAPM) states that the required premium on a risky asset will be proportional to its covariance with the returns on the market portfolio.[2] The model can be written in conditional form as

$$E_{t-1}(R_{i,t}) - \alpha = \lambda \ Cov_{t-1}(R_{i,t}, R_{m,t}), \qquad (1)$$

where, $R_{i,t}$, $R_{m,t}$ are ex-post returns on asset i and the market portfolio respectively, α is the rate of return on the risk-free asset, E_{t-1} and Cov_{t-1} are the conditional expectation and the conditional covariance given information at time t-1 and λ is the market risk premium per unit of market risk, i.e,

$$\lambda = [E_{t-1}(R_{m,t}) - \alpha]/ Var_{t-1}(R_{m,t}), \tag{2}$$

where, Var_{t-1} is the conditional variance. It is also equal to the representative investor's coefficient of relative risk aversion (see Merton 1973). The demand for shares of asset i by group A is given by,

$$Q_{A,i,t-1} = [E_{t-1}(R_{i,t}) - \alpha]/ \lambda\ Cov_{t-1}(R_{i,t}, R_{m,t}), \tag{3}$$

where, $Q_{A,i,t-1}$ is the percent of shares demanded by this group as of time t-1. If all investors behave according to (3) then $Q_{A,i,t-1} = 1$ and equation (3) reduces to the conditional CAPM given in (1). The demand for shares by positive feedback traders depends on last period's returns, i.e.,

$$Q_{B,i,t-1} = \varphi_{B,i}\ R_{i,t-1}, \tag{4}$$

where, $Q_{B,i,t-1}$ is the percent of shares demanded by group B as of time t-1. The extent of positive feedback trading is measured by $\varphi_{B,i} > 0$. If all investors follow positive feedback trading then the market will be unstable with prices at times exploding and at times collapsing. Finally, the demand of negative feedback traders is described by

$$Q_{C,i,t-1} = -\varphi_{C,i} \, R_{i,t-1}/Cov_{t-1}(R_{i,t}, R_{m,t}), \qquad\qquad (5)$$

where, $-\varphi_{C,i} < 0$ measures the extent of negative feedback trading and $Q_{C,i,t-1}$ the percent of shares demanded. This group of investors increase (decrease) their demand for shares after price declines (advances) in an attempt to exploit opportunities created by investors following positive feedback trading strategies. Their actions are clearly stabilizing since they reduce volatility induce by positive feedback. Their willingness to exploit opportunities however, is tempered by the degree of risk they are exposed to. Equivalently, their demand for shares is a decreasing function of covariant risk. This specification is in agreement with Shleifer and Summers (1990) who cite fundamental risk and resale price risk as factors preventing arbitrageurs from taking positions to fully eliminate the impact of noise traders.

In equilibrium all shares of asset i must be held, i.e., $Q_{A,i} + Q_{B,i} + Q_{C,i} = 1$. From (3), (4) and (5) it follows that the conditional risk premium for asset i can be written as

$$E_{t-1}(R_{i,t}) - \alpha = \lambda \, Cov_{t-1}(R_{i,t}, R_{m,t}) + [\lambda\varphi_{C,i} - \lambda\varphi_{B,i} \, Cov_{t-1}(R_{i,t}, R_{m,t})]R_{i,t-1}. \qquad\qquad (6)$$

Using a similar argument regarding the demand for shares of the market portfolio, the market premium can be written as

$$E_{t-1}(R_{m,t}) - \alpha = \lambda \, Var_{t-1}(R_{m,t}) + [\lambda\varphi_{C,m} - \lambda\varphi_{B,m} \, Var_{t-1}(R_{m,t})]R_{m,t-1}, \qquad\qquad (7)$$

where, covariant risk is substituted with market risk.[3] The generalized feedback model described by equations (1)-(7) suggests that in the presence of positive and negative feedback trading, conditional risk premia will diverge from those predicted by the CAPM. The degree of divergence can only be assessed empirically.

Expressions for ex-post returns for the market and asset i in standard regression form can be obtained by setting

$$R_{i,t} = E_{t-1}(R_{i,t}) + \varepsilon_{i,t}, \tag{8}$$

$$R_{m,t} = E_{t-1}(R_{m,t}) + \varepsilon_{m,t}. \tag{9}$$

Thus, the relevant regression equations are:

$$R_{i,t} = \beta_{i,0} + \beta_{i,1}\sigma_{i,m,t} + (\beta_{i,2} + \beta_{i,3}\sigma_{i,m,t})R_{i,t-1} + \varepsilon_{i,t} \tag{10}$$

$$R_{m,t} = \beta_{m,0} + \beta_{m,1}\sigma^2_{m,t} + (\beta_{m,2} + \beta_{m,3}\sigma^2_{m,t})R_{m,t-1} + \varepsilon_{m,t} \tag{11}$$

where, $\beta_{i,0} = \beta_{m,0} = \alpha$, $\beta_{i,1} = \beta_{m,1} = \lambda$, $\beta_{i,2} = \varphi_{C,i}\lambda$, $\beta_{i,3} = -\varphi_{B,i}\lambda\beta_{m,2} = \varphi_{C,m}\lambda$, $\beta_{m,3} = -\varphi_{B,m}\lambda$, $\sigma_{i,m,t-1} = Cov_{t-1}(R_{i,t}, R_{m,t})$ and $\sigma^2_{m,t} = Var_{t-1}(R_{m,t})$. If there is positive feedback trading then $\beta_{i,3}$ and $\beta_{m,3}$ will be negative and statistically significant. Similarly, the presence of negative feedback trading implies that $\beta_{i,2}$ and $\beta_{m,2}$ will be positive and statistically significant. Finally, significantly positive $\beta_{i,1}$ and $\beta_{m,1}$ would imply that there is a positive conditional risk-return tradeoff.

The common perception is that positive feedback trading causes positive autocorrelation in stock returns. The model with heterogeneous groups of investors however, suggests that the autocorrelation of returns will exhibit rather complex behavior assuming the covariance with the market returns is time-dependent. From (10) it can be seen that the first order autocorrelation, $\rho_{i,t}$, for the returns of asset i will be time dependent, i.e., $\rho_{i,t} = \beta_{i,2} + \beta_{i,3}\sigma_{i,m,t-1}$. Assuming as hypothesized that $\beta_{i,2} > 0$ and $\beta_{i,3} < 0$, the following relationships hold:

$$\text{if } \sigma_{i,m,t-1} < 0 \text{ then } \rho_{i,t} > \beta_{i,2} \tag{12a}$$

$$\text{if } \sigma_{i,m,t-1} = 0 \text{ then } \rho_{i,t} = \beta_{i,2} \tag{12b}$$

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$$\text{if } \sigma_{i,m,t-1} > \beta_{i,2}/\beta_{i,3} \text{ then } \rho_{i,t} < 0. \tag{12c}$$

Similar relationships hold for the first-order autocorrelation of the returns of the market portfolio. The model suggests that during volatile periods (i.e., high $\sigma_{i,m,t}$ and σ^2_t) first-order autocorrelations turn negative.[4] At the same time the portion of shares demanded by expected utility maximizers and negative feedback traders (groups A and B) decreases with a corresponding increase in the portion of shares demanded by positive feedback traders. Consequently, misspricing is more likely during those periods.

Estimation of the model requires parameterization of the conditional second moments of $R_{i,t}$ and $R_{m,t}$. Time variation in the second moments of stock returns have successfully been modeled via ARCH-type models (see, for example, Bollerslev, Chou and Kroner 1992). The particular model used for this purpose is a bivariate EGARCH model based on Nelson (1991) . There are two reasons for using this particular specification. First, it provides a natural nonegativity constraint for the parameters thus assuring that the covariance matrix will be positive semidefinite and second, it can captures possible asymmetries in conditional variances. Specifically, the elements of the covariance matrix are as follows:

$$ln(\sigma^2_t) = \alpha_{i,0} + \alpha_{i,1}\big(\big|z_{i,t-1}\big| - E\big|z_{i,t-1}\big| + \delta_i z_{i,t-1}\big) + \varphi_i ln(\sigma^2_{t-1}) \tag{13a}$$

$$ln(\sigma^2_t) = \alpha_{m,0} + \alpha_{m,1}\big(\big|z_{m,t-1}\big| - E\big|z_{m,t-1}\big| + \delta_m z_{m,t-1}\big) + \varphi_m ln(\sigma^2_{t-1}) \tag{13b}$$

$$\sigma_{i,m,t-1} = \rho_{i,m}\sigma_{i,t}\sigma_{m,t}, \tag{13c}$$

where, ln(.) are natural logarithms, $z_{i,t}$ and $z_{m,t}$ are normalized innovation and $\rho_{i,m}$ is the conditional correlation coefficient. Negative δ_i and δ_m would imply that negative returns are followed by higher volatility than positive returns of an equal size (see also Black 1978, Nelson 1991).

The model is estimated assuming conditional normality for the joint distribution of $R_{i,t}$ and $R_{m,t}$ and using the numerical optimization algorithm of Berndt et al. (1974).

III. Data and Empirical Findings

The data include daily returns for three size based portfolios (small, medium and large) as well as returns for the market index. All portfolios include NYSE, AMEX and NASDAQ firms and they are taken from the CRSP database. The sample period extends from 6/10/98 till 6/10/2005 for a total of 1761 observations.

Descriptive statistics for the daily returns on the four indices are reported in Table 1. These are the mean and the standard deviation, the Kolmogorov-Smirnov (K-S) nonparametric statistic for normality, first-order autocorrelation the Ljung-Box statistic testing the hypothesis that all autocorrelations up to the 10th lag are jointly zero and contemporaneous and lagged beta coefficients.[5] Average daily returns are statistically significant and approximately equal across portfolios. Pairwise correlations with the market proxy increase as we move to higher capitalizations suggesting that investors holding small capitalization portfolios were exposed to higher unsystematic risk. Another potentially important feature of the data set is that the market proxy leads both the portfolio of small and medium sized stocks. This can be seen from the lagged beta estimated by regressing the returns of each portfolio against lagged returns of the market proxy. The lagged beta is significant for the Small Cap and the Medium Cap portfolios. This is in agreement with Lo and MacKinlay (1990) who find that returns of high capitalization stocks can be used to predict returns of small stocks but not vice versa. The K-S statistics show significant departures from normality. Rejection of normality can be partially attributed to temporal dependencies in the moments of the series. The first-order autocorrelation is significant for small and medium size portfolios but not for the large size portfolio and the market proxy. This of course

does not preclude higher lag and higher order dependencies. In this respect, the LB statistic rejects in all instances the hypothesis that all autocorrelations up to the 10th lag are jointly zero. This provides evidence of temporal dependencies in the first moment of the distribution of returns. It is not clear to which extent positive and negative feedback trading contributes to these dependencies. More importantly, the LB statistic is incapable of detecting any sign reversals in the autocorrelations due to positive feedback trading. All it provides is an indication that first moment dependencies are present. Evidence on higher order (volatility) temporal dependencies is provided by the LB statistic when applied to the squared returns. It can be seen that for the squared returns this statistic is in general higher than the LB calculated for the returns suggesting that higher moment temporal dependencies are more pronounced. This of course is an empirical regularity encountered in almost all financial time series, especially in high frequencies. What is not clear from these statistics is the extent to which the two types of dependencies are linked i.e., whether the conditional variances (covariances) and autocorrelation are linked.

Table 2 reports maximum likelihood estimates of the model. The parameters describing the conditional variances are statistically significant in all instances at the 5% level at least suggesting that the variance-covariance matrices are time varying. More specifically, the conditional variances depend on past innovations and past conditional variances. The persistence of variance measured by φ is positively related to the portfolio size. There is evidence that volatility is in all instances an asymmetric function of past innovations rising proportionately more during price declines. Asymmetry is higher for smaller capitalization portfolios.

The coefficient measuring the conditional market price of risk, β_1, is significant for all portfolios. This is in agreement with the conditional CAPM but in contrast to other findings reported in the literature (see Bekaert and Wu 2000, Brandt and Kang 2004 and Ghysels, Santa-Clara and Valkanov 2005). Interestingly, the numerical values are very close to each other, even though no formal test of equality is attempted at this stage. For the small and medium capitalization

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portfolios, there is evidence of both positive and negative feedback trading. The signs of the relevant parameters β_2 and β_3 are as hypothesized by the model. No evidence of feedback trading is found for the high capitalization portfolio and the market portfolio. This supports the view of Black (1986) that noise traders are more likely to be found in small capitalization stocks. Inspection of equations (10) and (11) reveals that during high covariant risk periods positive feedback traders are more active. Given the nature of their strategy, mispricing is more likely during those periods. Interestingly, negative feedback traders, or, contrarians cannot take full advantage of positive feed back traders because risk during those periods is higher.

The diagnostics on estimated standardized residuals reported in Table 2 show no evidence of misspecification. They appear to be uncorrelated up to 10 lags and they pass the conditional normality test.

The time series properties of the estimated autocorrelations are explored further in Table 3. The average autocorrelation is inversely related to portfolio size. There is considerable time variation as can be gauged by the estimated standard deviation as well as the range. The estimated parameters of an AR(1) process suggests that autocorrelations are stationary and mean reverting. The speed of mean reversion in inversely related to size, i.e., higher capitalization portfolios exhibit higher autocorrelation persistence.

IV. Conclusion

This paper has addressed several limitations of earlier studies on feedback trading. Specifically, it has extended the conditional CAPM to incorporate the actions of three heterogeneous groups of investors: i) risk averse expected utility maximizers, ii) positive feedback traders and iii) negative feedback traders. The demand function for risky assets for the first group is compatible with the CAPM. Positive feedback traders are essentially trend chasers, i.e., they buy risky assets when prices move up and they sell them when prices move down. Negative feedback

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traders attempt to exploit positive feedback traders by buying low (i.e., during markets declines) and selling high (i.e., during market advances). They are however risk averse in the sense that their willingness to exploit mispricing is tempered by the amount of risk they are exposed to. The model is general enough to allow investigation of the interaction of the three groups at the aggregate (market) level as well as the individual asset level.

The findings are rather interesting. First, there is a positive conditional risk premium at both the market and the individual asset level. Second, there is evidence of both positive and negative feedback trading in small and medium capitalization stocks. Third, there is not evidence of either positive or, negative feedback trading in large capitalization stocks. Finally, the actions of feedback traders (positive and negative) are not significant at the market level.

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Table 1. Descriptive Statistics

	Small Cap	Mid Cap	Large Cap	Market
μ	0.0596*	0.0576*	0.0595*	0.0585*
σ	0.7169	0.7281	0.7614	0.7295
K-S	0.1415*	0.1139*	0.0302	0.0307
ρ_1	0.2146	0.1619	-0.0165	0.0136
LB(10)	96.1966*	71.4807*	24.0520*	30.0770*
$LB^2(10)$	94.4923*	71.4697*	234.307*	183.433*
$Corr(R_i, R_m)$	0.7093	0.8113	0.9809	1.0000
β	0.6972*	0.8097*	1.0238*	1.0000
β_{lagged}	0.1958*	0.1604*	-0.0123	0.0136

Notes: (*) Statistically significant at the 5% level at least. Sample period: 6/10/98-1/10/2005 (1,761 observations).

Table 2. Estimates of the Feedback Model

	Small Cap	Mid Cap	Large Cap	Market
β_0	-0.0656	-0.1001	-0.0218	-0.0216
	(-1.944)	(-2.631)*	(-0.637)	(-0.678)
β_1	0.1529	0.2379	0.1482	0.1429
	(3.170)*	(3.864)*	(2.173)*	(2.128)*
β_2	0.4264	0.3089	0.0292	0.1028
	(9.847)*	(5.380)*	(0.546)	(1.935)
β_3	-0.2365	-0.1837	-0.0608	-0.0951
	(-3.262)*	(-2.718)*	(-0.747)	(-1.091)
α_0	-0.1922	-0.1266	-0.0182	-0.0194
	(-7.481)*	(-6.041)*	(-3.601)*	(-3.553)*
α_1	0.2499	0.1588	0.1157	0.1221
	(7.866)*	(6.971)*	(8.857)*	(9.398)*
δ	-0.9178	-1.3229	-0.6417	-0.7025
	(-8.208)*	(-6.385)*	(-4.552)*	(-5.234)*
φ	0.7653	0.8335	0.9629	0.9652
	(26.041)*	(33.258)*	(148.52)*	(142.86)*
$\rho_{i,m}$	0.7007	0.7958	0.9809	1.0000
	(42.131)*	(55.520)*	(210.53)*	
LB(10)	5.3793	6.1316	9.1663	10.9368
LB^2(10)	4.2850	8.9480	3.5004	4.4490
K-S	0.0230	0.0230	0.0248	0.0248
R^2	0.0460	0.0230	0.0050	0.0050

Notes: (*) Statistically significant at the 5% level at least. Sample period: 6/10/98-1/10/2005 (1,761 observations).

Table 3. Time Series Properties of First-Order Autocorrelation.

	Small Cap	Mid Cap	Large Cap	Market
Panel A. Descriptive Statistics				
μ	0.3118	0.2168	-0.0035	0.0534
σ	0.0761	0.0583	0.0189	0.0302
$\rho_{t,min}$	-1.4393	-0.7092	-0.1939	-0.2955
$\rho_{t,max}$	3.3837	2.2778	0.0201	0.0887
Panel B. AR(1) Representation of First-Order Autocorrelation				
β_0	0.0838	0.0330	-0.0001	0.0030
	(16.328)*	(11.899)*	(-1.173)	(6.357)*
β_1	0.7311	0.8475	0.9587	0.9428
	(45.702)*	(68.121)*	(143.78)*	(120.66)*
R^2	0.5342	0.7182	0.9190	0.8889
DW	2.2041	2.1984	2.0186	2.0871

Notes: (*) Statistically significant at the 5% level at least.

ENDNOTES

1. DeLong, Shleifer, Summers and Waldman (1990) however, show that in an overlapping generations model noise traders can create significant nonfundamental risk in asset prices. By bearing the higher self-created risk, this group can earn a higher expected return than rational investors.

2. The model described in this section extends the work of Sentana and Wadhwani (1992), Shiller (1984) and (1990) and Cutler, Poterba and Summers (1991).

3. Here, the demand functions for shares of the market portfolio by groups A, B and C is given by $Q_{A,m,t-1}=[E_{t-1}(R_{m,t})-\alpha]/\lambda Var_{t-1}(R_{m,t})$, $Q_{B,m,t-1}=\varphi_{B,m}R_{m,t-1}$, and $Q_{C,m,t-1}=-\varphi_{C,m} R_{m,t-1}/Var_{t-1}(R_{m,t})$ respectively.

4. It should be noted that the model Cutler, Poterba and Summers (1990) also produces negative autocorrelation due to positive feedback trading for certain values of the parameters. Also Shiller (1989) shows that positive feedback trading can be associated with negative autocorrelation and higher risk.

5. The Kolmogorov-Smirnov statistic is calculated as $D_n = max|F_n(R)-F_0(R)|$ where F_n is the empirical cumulative distribution of R_t and $F_0(R)$ is the postulated theoretical distribution.
The Ljung-Box statistic for N lags is calculated as $LB(N)=T(T+2)\Sigma_{=1}(\rho/T-j)$ where ρ_j is the sample autocorrelation for j lags and T is the sample size.