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TIME-VARYING BETAS AND ASYMMETRIC EFFECTS OF NEWS: EMPIRICAL ANALYSIS OF BLUE CHIP STOCKS

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ABSTRACT

We investigate whether or not a beta increases with bad news and decreases with good news, just as does volatility. Using daily returns for nine stocks in a double beta model with EGARCH specifications, we show that news asymmetrically affects the betas of individual stocks. We find that betas depend on two source of news: market shocks and idiosyncratic shocks. Some stock betas depend on both while others depend on one. We categorize each stock return as belonging to one of three beta process models, a joint, an idiosyncratic, and a market model based on the role of market shocks and idiosyncratic shocks. Our conclusions differ from those of Brown, Nelson, and Sunnier (1995) who worked with monthly aggregated data in a bivariate EGARCH model. We believe that stock price aggregation in this previous research resulted in a loss of cross sectional variation and consequently lead to weak results. If the asymmetric effect is more readily apparent in daily data, then this may again explain previous researchers' inability to detect asymmetric effects. Our findings shed light on the controversy as to whether abnormalities in stock returns result from overreaction to information or from changes in expected returns in an efficient market. Finding an asymmetric effect in betas leads us to conclude that abnormalities can, at least partially, be explained by changes in expected returns through a change in beta.

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I. Introduction

Given evidence on the predictive asymmetry of volatility, we investigate whether or not a beta increases with bad news and decreases with good news, that is, whether an asymmetric / leverage effect exist.

Studies have documented the asymmetric effect of news on the volatility of stock returns. This "leverage or asymmetric effect" for individual stocks and market indices discovered by Black (1976) and confirmed by the findings of, e.g., French, Schwert and Stambaugh (1987), Nelson (1990) and Schwert (1990) refers to the fact that volatility tends to rise following negative returns and fall following positive returns. The asymmetric effect of news on volatility has been addressed in terms of two mechanisms: financial and operational leverage and determinants of market risk premium. First, financial and operational leverages capture the idea that if the value of a leveraged firm drops, then its equity becomes more highly leveraged, causing an increase in volatility[1] (Black (1976), and Christie (1982)). The second mechanism for the asymmetric effect focuses on the positive relation between volatility and the expected market risk premium (the expected return on a stock portfolio minus the riskless rates). If the expected market risk premium is an increasing function of market volatility, holding riskless rates

[1] Christie (1982) shows that equity volatility is increasing in financial leverage, and hence there is a negative relationship between the variance of returns and the value of equity. However, Christie (1982) and Black (1976) point out that financial and operational leverage is not enough to fully account for the asymmetry of volatility

constant, an increase in market volatility implies a increase in expected return and in return lowers the stock price, contributing to the asymmetric effect in volatility[2]

This evidence implies a way of explaining a time-varying beta. If the risk premium is an increasing function of the volatility, and beta is a measure of sensitivity to risk, then the asymmetric effect in volatility may imply such an effect in beta too.[3] The literature suggests that time variation of beta results from the variation in expected returns on the market portfolio and in relative risk of the firms' investment which causes financial or operational leverage. That is, if the beta of a leveraged firm's assets is positive then the beta of the firm's equity should rise in response to negative returns which increase the leverage of the firm. Thus, it is reasonable to expect equity betas to be increasing in leverage.[4] In addition, increases in market shocks to the firms also cause increases in beta and lead to an increase in expected returns on market. As a result, it should create a drop in the stock price (Ball and Kothari (1989)).

This paper extends Brown, Nelson, and Sunnier (1995, hereafter BNS) who work with monthly aggregated data in a bivariate EGARCH model. First, we explore the different roles of market and idiosyncratic shocks, which is ignored in the work of BNS.

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[2] See Pindyck (1984), Poterba and Summers (1986), French, Schwert and Stambough (1978), Bollerslev, Engle and Wooldridge (1988), Engel, Ng and Rothschild (1990), and Campbell and Hentschel (1992).

[3] Chou, Engle and Kane (1992) suggest another way to look at the time-varying beta. They estimate a time-varying parameter GARCH-M (TVP GARCH-M) model, which combines the GARCH-M model for the CAPM and the time-varying parameter model for measuring risk aversion. The basic ideas of this model are to explain the roles of risk aversion, to show the path of varying market beta over time, and to propose instrumental variables for risk aversion.

[4] Leverage is a decreasing function of equity returns, provided firms do not maintain dynamically constant market-valued capital structures. Maintaining a debt/equity ratio that is independent of equity returns would require continuous new issues or retirement of debt or equity. Firms would need to respond to share price declines with retirement of debt, which seems unlikely. Ball, Lev, and Watts (1976) provide evidence that such leverage adjustments do not occur immediately in response to earnings-induced leverage variation.

Since the beta of a firm measures sensitivity to risk, a series of abnormally negative returns caused by market and/or idiosyncratic shocks may increase the beta of a firm. Hence, the analysis of the asymmetric effects of news in betas gives specific information about individual stock returns. For this reason, our model distinguishes the role of market shocks and idiosyncratic shocks in determining asymmetric effects in a time-varying beta process.

Second, we use daily stock return data of individual firms rather than monthly aggregated data (portfolio or decile data) as used in BNS, to allow the separation of market shocks and idiosyncratic shocks. Since asymmetric responses of beta to good and bad news may be smoothed as the aggregated data is used, it is a more appropriate approach to examine individual stock return. Using daily data allows examination of the asymmetric effects in beta occurred in different frequency data.

Third, while BNS use a bivariate EGARCH model, we use a double-beta model (Engle and Merzrich (1996)) with an EGARCH variance specification. The double-beta model is suggested for parsimony and computability. In contrast to a bivariate EGARCH model, it directly uses market information to estimate the beta and variance of stock returns.

Using daily returns for nine stocks in a double beta model with EGARCH specifications, We find a strong asymmetric effect in beta as well as in volatility. As a result, it suggests the possible existence of a positive relation between beta and volatility of individual stock return since these may be related to each other through asymmetric effects to news.

We also find that betas depend on two source of news: market shocks and idiosyncratic shocks. Some stock betas depend on both while others just depend on one. We categorize each stock's beta as a one of three beta processes, a joint, an idiosyncratic, and a market model. The joint model for a beta process is for a stock return which beta is driven by market shocks and idiosyncratic shocks both. The idiosyncratic model explains the time-varying betas which have asymmetric effects in idiosyncratic shocks. The betas driven by market shocks belong to the market model.

Our conclusions differ from those of BNS (1995). Using monthly portfolio and decile data BNS find that asymmetric effects are absent in beta though they appear in volatility. We believe that stock price aggregation in this previous research resulted in a loss of cross sectional variation and consequently weak results. If the asymmetric effect is more readily apparent in daily data, then this may again explain previous researchers' inability to detect asymmetric effects.

Our results also shed light on the controversy over cross-sectional stock returns. The most significant challenge which time-varying beta models can address is found in the controversy of "abnormalities of stock prices".[5] This controversy involves two hypotheses: "overreaction to information" which causes the mispricing of the market (De Bondt and Thaler (1989), Chopra, Lakonishok and Ritter (1992)) versus the systematic changes in expected returns in an efficient market ((Chan (1989), Ball and Kothari (1989)).

De Bondt and Thaler (1989) and Chopra, Lakonishok and Ritter (1992, hereafter CLR) find evidence of mean-reversion in stock prices. That is, "losers," stocks that have recently experienced huge losses, tend to subsequently outperform "winners," stocks that have recently experienced price increases. They interpret this phenomenon as an overreaction of the kind assumed in an inefficient market[6] (such overreaction is inefficient; an investor exploits these inefficiency gains when stock prices revert to their respective fundamental value) and support the contrarian stock selection strategy that consists of buying stocks that have been losers and selling short stocks that have been winners. Many investment strategies, such as those based on the price/earnings ratio, or the books/market ratio can be regarded as variants of this strategy. CLR also support the overreaction hypothesis and show that this overreaction effect is stronger for smaller firms than larger firms.

However, Chan (1988) and Ball and Kothari (1989) argue that time-varying betas and risk premia can explain the return performance of winners and losers.[7] They find evidence that the beta of individual stock rises (falls) in response to abnormally negative (positive) returns. That is, there exists predictive asymmetry in conditional betas' response to shocks. Ball and Kothari argue that this asymmetric response to good and bad news explains the performance of winners and losers. They show that in an efficient

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[5] See Reid and Lanstein (1985), Fama and French (1988), Lo and MacKinlay (1988), Porterba and Summers (1988), Jegadeesh (1990), Lehmann (1990), Jegadeesh and Titman (1991) and Brock, Lakonishok and Le Baron (1992).

[6] Black (1986), Poterba and Summers (1987), DeBondt and Thaler (1895, 1987), and Lehmann (1990) support the inefficiency of market with the idea that the predictability of equity returns may reflect the overreaction of stock prices, the misperceptions of investors in an inefficient market.

[7] Zarowin (1990) supports market efficiency by analyzing return reversal behavior of stock prices. However, he relates it with size effect claiming that the tendency for losers to outperform winners is not due to investor overreaction, but to the tendency for losers to be smaller-sized firms than winners. He claims when losers are compared to winners of equal size, there is little evidence of any return discrepancy. He also shows that neither differences in risk nor in January returns can completely account for the return discrepancy. He concludes that the winner vs. loser phenomenon found by DeBondt and Thaler appears to be another manifestation of the size effect.

market time-varying expected returns are caused by variation in expected returns on the market portfolio, relative risk of a firm's investments, and leverage. Chan (1988) also explores the correlation between the betas and the market-risk premium in the contrarian strategy. He suggests that stocks whose values diminish become riskier on the basis of financial leverage effect. From option pricing theory, a change in firm value has a bigger effect on the market values of equity than on the market value of debt like liabilities of the firm. Thus, barring any offsetting actions taken by the firm, the financial leverage of the loser firm becomes bigger as the stock price falls, increasing the risk of the stock. Likewise this leverage effect reduces the risk of a winner stock. Hence, the loser's beta is positively correlated with the market risk premium, whereas the winner's is negatively correlated with it.

By finding a weak asymmetric effect in beta, BNS support the overreaction theory by finding no leverage effect in beta. BNS conclude that betas are not responsive enough to account for the differing return performances of "winners" and "losers" and support De Bondt and Thaler's claim. However, finding an asymmetric effect in betas leads us to conclude that abnormalies can be explained by changes in expected returns through a change in beta supporting the claim of Chan and Ball and Kothari.

In this paper, the time-varying beta of individual firm stock returns is investigated in the context of an asymmetric effect of news, market shocks and idiosyncratic shocks. Focusing on these two shocks, we suggest a model that allows one to distinguish two shocks in the beta process. We use the double beta model with EGARCH variance specification. The double beta model specification is used for parsimonious estimation and computability. In this model market information is used as an explanatory in the estimation of the volatility and beta of the individual stock returns. For the empirical analysis the daily data of twenty five firms' stock traded in NYSE and NASDAQ are chosen. The stocks are those most widely held: Apple, AT&T, Bank of America, Bell Atlantic, Chase, Coca-Cola, Compaq, Disney, Ford, Exxon, GAP, General Electric, Hewlett Packard, IBM, Intel, Johnson & Johnson, JP Morgan, McDonald, Merck, Microsoft, Motorola, Nordstrom, Sears, Sun, and Time Warner. We categorize each stock's beta into three beta models based on role of two shocks, market shocks and idiosyncratic shocks. They are a joint model, an idiosyncratic model, and a market model.

The remainder of this paper is organized as follows: Section II provides the specification of the double beta model with EGARCH variance. Section III describes the data of nine firms and the testing procedure. The behavior of time-varying beta associated with asymmetric effect for each firm is examined and the empirical results are summarized in Section IV. Section V concludes.

II. Model Specification

for Time-Varying Beta in Double-Beta Model with EGARCH Variance

Let $r_{m,t}$ and $r_{i,t}$ be the demeaned returns on the market and on the individual firm stock i at time t.

$$r_{m,t} = \sigma_{m,t} \cdot z_{m,t} \quad (1)$$

$$r_{i,t} = \beta_{i,t} \cdot r_{m,t} + \sigma_{i,t} \cdot z_{i,t} \quad (2)$$

where $z_{m,t}$ and $z_{i,t}$ are uncorrelated i.i.d. processes with zero means and unit variances. Here, $\sigma_{m,t}, \sigma_{i,t}$, and $\beta_{i,t}$ are, respectively, the conditional variance of $r_{m,t}$, the firm-specific variance of $r_{i,t}$, and the conditional beta of $r_{i,t}$ with respect to $r_{m,t}$. Beta is expressed in the following way:

$$\beta_{i,t} = \frac{E_{t-1}[r_{i,t} \cdot r_{m,t}]}{E_{t-1}[r_{m,t}{}^2]} \quad (3)$$

where $E_{t-1}[\cdot]$ denotes expectation at time t-1.

Equation (2) turns out to be the one factor model of Engle, Ng, and Rothschild (1990)[8] where $\beta_{i,t} \cdot r_{m,t}$ is the market factor in $r_{i,t}$ with conditional variance $\beta^2_{p,t} \cdot \sigma^2_{m,t}$, while $\sigma_{i,t} \cdot z_{i,t}$ is the firm-specific component of risk with conditional variance $\sigma^2_{i,t}$. This model implies that the individual excess return consists of two components, the market factor effect and its idiosyncratic effect. By assumption, these two components of

[8] Engle, Ng, and Rothschild (1990) suggested the factor model as a parsimonious structure for the conditional covariance matrix of asset excess returns. The basic idea of this model is that the volatility of individual stock returns can be decomposed in two components, a systematic and an idiosyncratic one. The systematic component is explained with the volatility of market return while idiosyncratic one shows its own volatility that is not captured by the market.

returns are uncorrelated. The variance of the return is then given as the square of the market beta times the market volatility plus the variance of the idiosyncratic error.

One of the applications for a factor model for an individual stock is the double beta model, which has one beta in the mean and another beta in the idiosyncratic variance. Letting the idiosyncratic error itself be a univariate EGARCH process, the double beta model of individual stock returns can be estimated by univariate EGARCH variance with the market volatility as an input (Engle and Mezrich (1996)). Compared to the bivariate EGARCH specification of BNS, this model is relatively parsimonious since it uses market information directly in order to estimate beta and volatility of individual stock returns. First, the volatility of market return is specified as an EGARCH process. Second, beta and volatility of an individual firm are simultaneously estimated with its own EGARCH variance specification using the market volatility as a regressor in the individual variance equation. Here, the double beta model is chosen for model specification as a factor model.

In order to estimate the double beta model, the market conditional variance must be specified. We assumed that the market conditional variance $\sigma^2_{m,t}$ follows a univariate EGARCH(1,1) process. That is,

$$\ln(\sigma^2_{m,t}) = \alpha_m + \delta_m \cdot [\ln(\sigma^2_{m,t-1}) - \alpha_m] + \theta_m \cdot z_{m,t-1} + \gamma_m [|z_{m,t-1}| - \mathrm{E}|z_m|] \qquad (4)$$

By construction, $\theta_m \cdot z_m$ and $\gamma_m [|z_m| - \mathrm{E}|z_m|]$ are innovations in $\ln(\sigma^2_{m,t+1})$. The $\theta_m \cdot z_m$ term in (4) allows for leverage effects. When $\theta_m < 0$, $\ln(\sigma^2_{m,t})$ tends to rise (fall) following the nagative market shock z_m which drops (rises) in prices. If $\gamma_m > 0$, the $\gamma_m[|z|-E|z|]$ term raises (lowers) $\ln(\sigma^2_{m,t})$ when the magnitude of a market shock is larger (smaller) than expected. Taken together, terms $\theta_m \cdot z_m$ and $\gamma_m[|z|-E|z|]$ allow the market's conditional variance to respond asymmetrically to positive and negative returns.

For the firm-specific return, a univariate EGARCH(1,1) conditional variance $\sigma^2_{i,t}$ in the double beta model is changed to

$$\ln(\sigma^2_{i,t}) = \alpha_i + \delta_i \cdot [\ln(\sigma^2_{i,t-1}) - \alpha_i] + \theta_i \cdot z_{i,t-1} + \gamma_i[| z_{i,t-1} | - E | z_i |] + \delta_{i,m} \ln(\sigma^2_{m,t}) \quad (5)$$

Here the appearance of a market volatility term $\ln(\sigma^2_{m,t})$ in the volatility process of individual stock return constitutes the difference between the double-beta model and the bivariate EGARCH model. The market volatility is incorporated as a regressor in the double-beta model. It means that market information feeds directly into the volatility of the individual stock return. The intuition for the functional form of (5) is similar to that for (4). If $\theta_i < 0$ and $\gamma_i > 0$, then the firm-specific conditional variance rises (falls) in response to negative firm-specific shocks and in response to firm-specific shocks of larger (smaller) magnitude than expected.

The model for conditional beta, $\beta_{i,t}$, is constructed assuming an AR(1) process.[9]

$$\beta_{i,t} = \alpha_\beta + \delta_\beta \cdot [\beta_{i,t-1} - \alpha_\beta] + \lambda_i \cdot z_{i,t-1} + \lambda_m \cdot z_{m,t-1} \quad (6)$$

The $\lambda_i \cdot z_i$ and $\lambda_m \cdot z_m$ terms allow for leverage effects in the conditional betas which is suggested by Chan (1988) and Ball and Kothari (1989). If λ_i is negative, the conditional beta rises in response to negative idiosyncratic returns (non-market returns) and drops in response to positive idiosyncratic returns. Similarly, if λ_m is negative, the conditional beta rises in response to negative market returns and drops in response to positive market returns.

Finally, in order to implement the estimation, models for beta, the volatility of market return and the volatility of individual stock return are specified in equations (4), (5) and (6). For a given initial parameters and initial values of $\{r_{m,t}\}$ and $\{r_{i,t}\}$, we can easily derive the $\{z_{m,t}\},\{z_{i,t}\},\{\sigma^2_{m,t}\},\{\sigma^2_{i,t}\}$ and $\{\beta_{i,t}\}$ sequences by computing the quasi-likelihood functions recursively. The initial values are set to their unconditional expectations.

III. Empirical Applications

1. Data

For this empirical analysis we use the daily stock returns of Apple, AT&T, Bank of America, Bell Atlantic, Chase, Coca-Cola, Compaq, Disney, Ford, Exxon, GAP,

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[9] BNS also choose AR(1) order for the bivariate system.

General Electric, Hewlett Packard, IBM, Intel, Johnson & Johnson, JP Morgan, McDonald, Merck, Microsoft, Motorola, Nordstrom, Sears, Sun, and Time Warner. The data is from January 1, 1990, to December 29, 1995, and comes from the New York Stock Exchange (NYSE).[10] In order to estimate the market return the S&P500 index of the same period is used. Those prices are transformed into returns and are demeaned by its unconditional mean.

2. Testing and Model Selection for Beta

Investigating the beta process yields the information on how individual stock returns behave. In reality, individual stock returns respond to shocks differently. This gives the insight that each beta process may be characterized by the relative importance of the two shocks, market shocks and idiosyncratic shocks. Three models of different beta specifications are estimated for individual stock returns.

Joint Model :
$$\beta_{i,t} = \alpha_\beta + \delta_\beta \cdot (\beta_{i,t-1} - \alpha_\beta) + \lambda_i \cdot z_{i,t-1} + \lambda_m \cdot z_{m,t-1}$$

Idiosyncratic model :
$$\beta_{i,t} = \alpha_\beta + \delta_\beta \cdot (\beta_{i,t-1} - \alpha_\beta) + \lambda_i \cdot z_{i,t-1}$$

Market Model :
$$\beta_{i,t} = \alpha_\beta + \delta_\beta \cdot (\beta_{i,t-1} - \alpha_\beta) + \lambda_m \cdot z_{m,t-1}$$

[10] Stock prices are transformed into stock returns using the following formula.

$$r_{i,t} = \frac{p_{i,t} - p_{i,t-1}}{p_{i,t-1}}$$

The joint model considers the leverage effects of idiosyncratic shock, z_{it-1} and market shock, z_{mt-1}. If λ_i is significantly less than zero, it could be that there exists a leverage effect of idiosyncratic shocks in beta process. If there is bad news in the market and such shocks have an asymmetric effect, λ_m, should be significantly negative. Here, with significance of the coefficients, λ_i and λ_m, the arguments of Chan (1988) and Ball and Kothari (1989) can be examined. In the idiosyncratic model market shocks $z_{m,t-1}$ is omitted to test the significance of market shocks in joint model. The market model is estimated to test the significance of idiosyncratic shocks $z_{i,t-1}$ in joint model.

The estimation procedure follows the "general to simple rule" applying the LR (log likelihood) test. Model selection between joint model and idiosyncratic model is based on testing how the market volatility affects beta.[11]

$$H_0 : \lambda_m = 0$$

$$H_a : \lambda_m \neq 0$$

Market model only examines the effect of market volatility on the beta process. If the beta process of specific stock return is applied to market model against joint model,

[11] If the test can not reject H_0, idiosyncratic model is chosen and it implies that beta process is driven by idiosyncratic shocks. According to the LR test,

$$-2 \cdot (LR_R - LR_U) \sim \chi^2(h)$$

where LR_R is the log likelihood value of the restricted model
LR_U is the log likelihood value of the unrestricted model
h is the number of restrictions.

If the value of $-2 \cdot (LR_R - LR_U)$ is smaller than 3.84, which is the tabulated value of $\chi^2(1)$ for a 95 percent confidence interval for λ_m, then the null hypothesis can not be rejected.

then market shocks induce the change in the beta, which implies that the coefficient of z_{it-1}, the idiosyncratic shocks, is zero under the null hypothesis.

$$H_0 : \lambda_i = 0$$

$$H_a : \lambda_i \neq 0$$

These tests have an additional benefit: one can verify the possibility of multicollinearity of the market shock, z_{m-1}, and idiosyncratic shock, z_{i-1} in joint model. Multicollinearity may occur because market information is directly used for the estimation of beta and volatility of individual stock return. In that case, both may incorporate each other to some extent, even though in theory these two terms should be independent of each other. Multicollinearity might result in the insignificance of the coefficients of those variables, whereas a fit with each of them alone might produce a significant coefficient. Therefore, only looking at the general model, Joint model, may give incorrect information regarding the importance of these shocks in the beta process.

IV. Results - Empirical Analysis of Nine Firms

Using daily data for nine firms, we find that the time-varying beta as well as volatility of an individual stock return has asymmetric effects of news, market shocks and/or idiosyncratic shocks. The summary of the empirical analysis is presented in table

1. In table 1 each stock's beta is categorized as one of three beta processes: a joint, an idiosyncratic or a market model.

Table 2 reports the model selection and the parameter estimates for beta and conditional variance for each of the nine firms. The results are summarized in the graphs in Figures 1 to 25. Each figure consists of the stock price, the estimated betas from the double-beta model with EGARCH, and the conditional variance of each stock return and.

1. Time-varying beta and time-varying variance

These results lead to the following conclusions. First, the empirical results support that time-varying betas are driven by the asymmetric effect of news. The results can be characterized into three categories such as joint, idiosyncratic and market model. For those models, the asymmetric effect is present as beta increases with goods news and decreases with bad news.

Joint model is the beta series that idiosyncratic and market shocks both induce the time-varying betas. One can see increases of betas as there is bad news of market or individual firm itself while decreases of betas result from good news. Following the "general to simple rule", idiosyncratic model and market model are rejected against joint model, even though in some series such as Coca-Cola the two shocks, market and idiosyncratic shocks, seem to be multicollinear. The series of Coca-Cola, Merck, General Electric, Sears, Bank of America, Hewlett Packard, GAP, JP Morgan, McDonald, Intel, Compaq, Chase, and Ford belong to this joint model according to an LR test.[12] (See figure 1 to 13.)

Idiosyncratic model is applied when idiosyncratic shocks are the main reason for the asymmetric effect, since bad idiosyncratic news increases the betas while good news decrease the betas. LR test shows that Exxon, Microsoft, Apple, Johnson & Johnson, and Sun belong to the model.[13] (See figure 14 to 18.)

Market model is defined as the process wherein beta is driven by market shock. Betas of Disney, Bell Atlantic, Nordstrom, and Time Warner increase with bad market news and decreases with good market news. Market model is chosen against joint model, since the LR test for the significance of idiosyncratic shocks fails.[14] One feature of this stock is a small and weak leverage effect in conditional variance. Given the choice of market model, this weak leverage effect in its own conditional variance is what is expected and is further evidence of the existence of a positive relation between beta and volatility of individual stock returns. (See figure 20 to 23.)

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[12] The time-varying betas of Coca-Cola were induced by both market and idiosyncrasies even though market shocks were the main reason for the change of beta during the time period examined. (See figure 1.) Merck experienced a price fall during 1992 when the market was in a boom. However, in most of the remaining periods changes in prices present a similar pattern to that of the market. During late 1990 the market shocks increased beta and the bad idiosyncratic shocks caused beta to increase during late 1992 to 1993. (See figure 2.) Most of the shocks to General Electric's stock returns also came from the market while the idiosyncrasies were found in some periods. (See figure 3.) Most of Sears' shocks came from the market, but it experienced good idiosyncratic news in late 1993. The asymmetric effect of bad market shocks increased the beta while good idiosyncratic shocks induced the increase in beta. (See figure 4.) Once again, one can see the role of two shocks of the asymmetric effects in betas.

[13] A lot of idiosyncratic shocks occurred on Exxon stock returns during the periods examined, especially bad shocks. (See figure 14.)

[14] The existence of idiosyncratic shocks as a regressor in joint model does not make a difference in the explanatory power of joint model compared to market model to support the result that the time-varying beta of Disney stock is explained by the market shocks through an asymmetric effect.

These results imply that the weak leverage effect in BNS's finding results from their analysis of aggregated data rather than the individual firm data used here. That is, aggregated data loses much of the cross-sectional variation in individual firm betas. Therefore, it is desirable to model conditional variance and beta at the individual firm level.

Second, the frequency of data should be emphasized in analyzing time-varying beta. Asymmetric effects in betas are more apparent in high frequency data (daily data) than in low frequency data (monthly). It may be another possible reason why BNS does not have significant asymmetric effects in betas.

Third, the analysis of both idiosyncratic and market shocks provides a better understanding of individual stock returns' characteristics. For this purpose, the model distinguishing these two shocks should be emphasized since the betas of individual stock returns can be categorized based on the analysis of which shocks dominate the beta process. Such analysis may give information regarding such things as hedging strategies, which we have not explored. The different types of time-varying betas of individual firms suggest that it is useful to form a portfolio for investment based on this information. For example, a stock whose beta is driven by its own idiosyncrasy can be hedged against a stock for which market shocks dominate the beta.

Fourth, the asymmetric effect in variance itself is also found in market returns and individual stock returns. The volatility of market and individual stock returns increase with good news and decrease with bad news in the double-beta model with EGARCH variance. However, this is not a surprising result since this phenomenon has been addressed in the literature with different model settings. It leads to the implication that there may exists a positive relation between beta and volatility through a leverage effect.[15]

Last, these results address the controversy of "abnormalities of stock returns". The observed phenomenon of stock return mean reversal is explained by two competing hypothesis: predictable changes in the expected return in efficient market and stock price overreaction in inefficient market.

De Bondt and Thaler (1985) present the evidence of return reversal over long periods. In particular, stocks that experience poor performance tend to outperform winners during the subsequent years. They interpret the evidence as a manifestation of irrational behavior by investors, which they term "overreaction". However, according to Chan (1988) and Ball and Kothari it is due to systematic changes in expected returns and expected returns on extreme winners and losers vary substantially follows from pronounced changes in leverage. Consistent with the prediction of the leverage hypothesis, Ball and Kothari report that the betas of extreme losers exceed the betas of extreme winners in subsequent years. Such a large difference in betas, coupled with historical risk premiums, can account for substantial differences in realized returns.

The results of this paper support the efficiency market hypothesis since the betas change asymmetrically in response to news. BNS support the overreaction hypothesis based on the result of insignificant asymmetric time-varying beta. However, when different data of different time frequency is used, the asymmetric effect in beta becomes significant implying the changes in expected returns. This results seems interesting since

[15] There may exist the asymmetry in beta's speed of adjustment to the news. While the beta seems to adjust quickly to bad news, its response to good news looks slow. Once the beta increases, even after the good news, it takes longer to decrease. This tendency can also be found

there exists an argument that the systematic changes in return may not happen in the short run data.

2. Model specification for time-varying beta process

It is necessary to test for the AR(1) specification in the beta process since stocks such as Motorola and AT&T may have the leverage effect of market or idiosyncratic shocks in beta when beta is specified as a different AR order process.

Motorola had a lot of idiosyncratic shocks during the 1990s. The joint model is chosen by the LR test. However, contrary to theory the coefficients of the two shocks in the joint model have a positive sign. The market shocks dominated the AT&T stock return during the 90s, and as a result, the market model seems a reasonable model specification for beta. However, in none of the models are any of the coefficients significant.

One interpretation for these results is incorrect specification of AR(1) for beta since AR(1) terms have such large standard errors. In this case, the incorrect order of beta's AR leads to incorrect information about other regressors, two shocks $z_{i,t-1}$ and $z_{m,t-1}$. Another interpretation is the absence of asymmetric effect in beta. In order to evaluate these two interpretations, the new model for beta with a different order should be estimated.

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in the volatility and seems to be another evidence for a positive relation between betas and volatilities through the asymmetric effect.

$$\beta_{i,t} = \alpha_{\beta,t} + \sum_{j}^{k} \delta_{i,j} \cdot (\beta_{i,t-j} - \alpha_{\beta}) + \lambda_i \cdot z_{i,t-1} + \lambda_m \cdot z_{m,t-1} \qquad (7)$$

where $j \neq 1$ and $k < \infty$

For the empirical test, zero order for AR in beta is chosen. The reason we include no autoregressive term in beta is that this model gives a rough indication of whether shocks in beta have a leverage effect.[16] If the coefficients of these shocks are negative and significant, then we see the evidence of an asymmetric effect. The model specification is transformed to,

Joint model′ : $\beta_{i,t} = \alpha_{\beta,t} + \lambda_i \cdot z_{i,t-1} + \lambda_m \cdot z_{m,t-1}$[17] (8)

Idiosyncratic model′ : $\beta_{i,t} = \alpha_{\beta} + \lambda_i \cdot z_{i,t-1}$ (9)

Market model′ : $\beta_{i,t} = \alpha_{\beta} + \lambda_m \cdot z_{m,t-1}$ (10)

Idiosyncratic model′ and market model′ provide the same tests for joint model′ as idiosyncratic and market models provided for joint model.

In the case of Motorola, idiosyncratic model′ has a significant and negative coefficient, λ_i, implying that the beta process is driven by its own idiosyncratic shocks. This appears reasonable since stock returns of Motorola have a lot of idiosyncrasies. These results support the first interpretation, that if we find the correct order of AR as

[16] However, this specification gives the beta extreme volatility. Considering a beta process is time-dependent it does not seem to be a realistic model.

[17] Here $\alpha_{\beta,t}$ is the unconditional mean of beta and the OLS estimate was used as its initial value.

specification for beta, then it will have significant asymmetric effect of idiosyncratic shocks in beta. (See figure 19.) For AT&T, market model′ provides evidence to support the argument since it has significantly negative value of the coefficient of the market shocks. It is not a surprising result since the stock returns of AT&T were dominated by market shocks. (See figure 24.) Therefore, these results support the first interpretation of the leverage effect in beta on the condition that the correct specification for the AR order of beta is suggested. As a result, Motorola is categorized as idiosyncratic model while AT&T belongs to market model.

However, there seem to be stocks where the asymmetric effect may not be apparent in betas. Those stocks are categorized into constant beta model. IBM had large, bad idiosyncratic news, and moved in the opposite direction of the market. Idiosyncratic model is a reasonable candidate since it has greater log likelihood value than other model types. However, it has an insignificant AR(1) coefficient and a positive coefficient for idiosyncratic shocks. It also gives two interpretations as in the case of Motorola and AT&T above. First, the incorrect specification for the AR order in beta is the reason for this result. Second, no asymmetric effect can explain the movement of beta over time.

Those models are estimated for evaluation of these interpretations. If the coefficient of $z_{i,t-1}$, the idiosyncratic shock which dominated the stock return of IBM, has a negative value, then there may be a leverage effect of idiosyncrasy in beta. The estimation results of joint model′ and market model′ show the significance of these two shocks in beta. However, the idiosyncratic shock still has a positive coefficient while the market shock has a negative coefficient. Therefore, stocks such as IBM seem to support the second interpretation that there may be no leverage effect in betas and we categorize IBM stock as a constant beta process.

V. Conclusion

We investigate whether or not a beta increases with bad news and decreases with good news, just as does volatility. Focusing on the roles of market and idiosyncratic shocks, which is ignored in BNS's work, we use daily returns for nine stocks in a double beta model (Engle and Merzrich (1996)) with EGARCH specifications.

Contradictory to BNS's results, we show that news asymmetrically affects betas of individual stocks. It is desirable to model conditional covariances and beta at the individual firm level. We also find that betas depend on two sources of news: market shocks and idiosyncratic shocks. Some stock betas depend on both while others only depend on one. It enables us to categorize each stock's beta as one of three beta processes. They are the joint model, the idiosyncratic model, and the market model. The asymmetric effects of news may, in turn, provide the mechanism by which relate the betas and volatilities positively. Furthermore, these effects are more apparent in high frequency data (daily data) rather than in low frequency data (monthly data).

We believe that stock price aggregation in BNS results in a loss of cross sectional variation and consequently leads to weak results. If the asymmetric effect is more readily apparent in daily data, then this may again explain BNS's inability to detect asymmetric effects.

Our findings shed light on the controversy of whether abnormalies in stock returns results from overreaction to information or stems from changes in expected returns in an efficient market. Finding an asymmetric effect in betas leads us to conclude that abnormalies can, at least partially, be explained by changes in expected returns through a change in beta.

The results may be also useful in other contexts that we have not explored. They seem to be a potentially useful tool for investigating some hedging strategies since the property of individual stock returns can be inferred from the analysis of a beta process. The different types of time-varying betas of individual firms suggest a strategy for forming a investment. portfolio. For example, a stock whose beta is driven by its own idiosyncrasy can be hedged with a stock for which market shocks dominate the beta. Further investigation of this is left for future studies.

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$$\ln(\sigma_{i,t}^2) = \alpha_i + \delta_i \cdot [\ln(\sigma_{i,t-1}^2) - \alpha_i] + \theta_i \cdot z_{i,t-1} + \gamma_i [| z_{i,t-1} | - E | z_i |] + \delta_{i,m} \ln(\sigma_{m,t}^2)$$

$$\beta_{i,t} = \alpha_\beta + \delta_\beta \cdot [\beta_{i,t-1} - \alpha_\beta] + \lambda_i \cdot z_{i,t-1} + \lambda_m \cdot z_{m,t-1}$$

Firm	Model	α_β	δ_β	λ_I	λ_m	α_I	δ_I	θ_i	γ_I	$\delta_{I,m}$
COCA COLA	**Joint**	1.0669	0.9970	-0.0124	-0.0101	-8.5683	0.8702	-0.077	0.099	0.006
	-12650.51	0.0623	0.4743	0.0059	0.0067	0.7034	1.5392	0.024	1.197	1.926
MERCK	**Joint**	1.1031	0.9635	-0.0314	-0.0209	-8.2914	0.9916	-0.038	0.054	0.000
	-12210.95	0.0456	0.3918	0.0161	0.0107	0.3126	0.4661	0.012	0.613	0.768
General Electric	**Joint**	1.0593	0.9950	-0.0238	-0.0077	-8.4260	0.9702	-0.033	0.128	0.003
	-13238.80	0.0423	0.3399	0.0073	0.0053	1.2525	0.5606	0.017	0.239	1.540
SEARS	**Joint**	0.5248	0.9999	-0.0056	-0.0225	-7.5965	0.8995	-0.002	0.218	0.007
	-11555.67	0.0005	0.0043	0.0000	0.0000	0.0036	0.0004	0.000	0.000	0.005
Bank of America	**Joint**	0.9721	0.9995	-0.0096	-0.0151	-7.5476	-0.0401	0.1954	0.9675	0.0068
	-12497.42	0.0804	0.0005	0.0030	0.0029	0.4742	0.0056	0.0103	0.0033	0.0017

Firm	Model	α_β	δ_β	λ_l	λ_m	α_i	δ_l	θ_i	γ_i	$\delta_{l,m}$
CHASE	**Joint**	1.3003	0.9948	-0.0052	-0.0020	-8.3965	-0.0322	0.0629	0.9967	0.0011
	-11137.13	0.0359	0.0116	0.0005	0.0004	0.1745	0.0026	0.0050	0.0007	0.0001
HP	**Joint**	1.4594	0.9943	-0.0050	-0.0225	-8.4564	-0.0297	0.0350	0.9957	0.0003
	-10930.38	0.0520	0.0040	0.0006	0.0055	0.0739	0.0020	0.0034	0.0006	0.0001
GAP	**Joint**	1.1507	0.9989	-0.0162	-0.0135	-7.6701	-0.0979	0.1006	0.6108	0.0009
	-10386.56	0.0944	0.0005	0.0030	0.0048	0.3235	0.0123	0.0191	0.0613	0.0124
JP Morgan	**Joint**	0.0452	0.9954	-0.0023	-0.0015	-8.3328	0.0363	0.2498	0.9423	0.0110
	-13766.15	0.0168	0.0060	0.0002	0.0001	0.3134	0.0061	0.0097	0.0041	0.0022
McDonald	**Joint**	1.0444	0.9931	-0.0030	-0.0074	-9.1733	-0.0262	0.1283	0.9440	0.0002
	-12163.36	0.0317	0.0098	0.0000	0.0037	0.4714	0.0068	0.0099	0.0083	0.0026
INTEL	**Joint**	1.7570	0.9984	-0.0012	-0.0249	-8.2547	0.0025	0.1149	0.9583	0.0001
	-10661.45	-0.0914	0.0010	0.0005	0.0043	0.2143	0.0048	0.0099	0.0063	0.0009
COMPAQ	**Joint**	1.4506	0.9962	-0.0053	-0.0207	-7.6734	-0.0650	0.0289	0.9846	0.0000
	-10007.70	0.0894	0.0040	0.0029	0.0057	0.1850	0.0035	0.0039	0.0015	0.0003
FORD	**Joint**	1.0745	0.9998	-0.0001	-0.0094	-8.9810	-0.0191	0.0140	0.9968	0.0000
	-11464.29	0.0610	0.0005	0.0000	0.0031	0.0562	0.0016	0.0026	0.0007	0.0001

1. Standard errors are estimated using Newey-West heteroskedasticity estimator and appear below the coefficient estimates.
2. Log likelihood values are presented below the model specification

<TABLE 3> DOUBLE BETA MODEL PARAMETER ESTIMATES (IDIOSYNCRATIC MODEL)

$$\ln(\sigma^2_{i,t}) = \alpha_i + \delta_i \cdot [\ln(\sigma^2_{i,t-1}) - \alpha_i] + \theta_i \cdot z_{i,t-1} + \gamma_i [|z_{i,t-1}| - E|z_i|] + \delta_{i,m} \ln(\sigma^2_{m,t})$$

$$\beta_{i,t} = \alpha_\beta + \delta_\beta \cdot [\beta_{i,t-1} - \alpha_\beta] + \lambda_i \cdot z_{i,t-1}$$

Firm	Model	α_β	δ_β	λ_i	λ_m	α_i	δ_i	θ_i	γ_i	$\delta_{i,m}$
EXXON	**Idiosyncratic**	0.7538	0.9980	-0.0170		-8.4796	0.8800	0.046	0.165	0.009
	-12994.92	0.0728	0.9103	0.0091		0.4471	0.4271	0.026	0.249	0.687
MICRO SOFT	**Idiosyncratic**	1.4265	0.9722	-0.0372		-7.3594	-0.0700	0.1482	0.9065	0.0093
	-11029.56	0.0358	0.0128	0.0093		0.2625	0.0088	0.0126	0.0117	0.0028
APPLE	**Idiosyncratic**	1.5113	0.9979	-0.0180		-7.5182	-0.1194	0.4605	0.3906	0.0004
	-10027.55	0.0696	0.0018	0.0028		0.3034	0.0107	0.0173	0.0329	0.0182
Johnson & Johnson	**Idiosyncratic**	1.1057	0.9935	-0.0050		-9.4463	-0.0427	0.1426	0.9635	0.0004
	-11293.36	0.0234	0.0077	0.0017		0.3500	0.0066	0.0102	0.0035	0.0013
SUN	**Idiosyncratic**	1.7971	1.0000	-0.0163		-4.2686	-0.1199	0.2397	0.7479	0.0769
	-9627.06	0.0565	0.0007	0.0031		0.2859	0.0095	0.0161	0.0233	0.0106
MOTOROLA	**Idiosyncratic**	1.3098		-0.1678		-5.4950	0.9831	-0.0397	0.0591	0.0039
	-11126.32	0.0015		0.0019		0.0596	0.0171	0.0004	0.0131	0.0295

1. Standard errors are estimated using Newey-West heteroskedasticity estimator and appear below the coefficient estimates.
2. Log likelihood values are presented below the model selection.

<TABLE 4> DOUBLE BETA MODEL PARAMETER ESTIMATES (MARKET MODEL)

$$\ln(\sigma_{i,t}^2) = \alpha_i + \delta_i \cdot [\ln(\sigma_{i,t-1}^2) - \alpha_i] + \theta_i \cdot z_{i,t-1} + \gamma_i [| z_{i,t-1} | - E | z_i |] + \delta_{i,m} \ln(\sigma_{m,t}^2)$$

$$\beta_{i,t} = \alpha_\beta + \delta_\beta \cdot [\beta_{i,t-1} - \alpha_\beta] + \lambda_m \cdot z_{m,t-1}$$

Firm	Model	α_β	δ_β	λ_i	λ_m	α_i	δ_i	θ_i	γ_i	$\delta_{i,m}$
DISNEY	**Market**	1.0434	0.9926		-0.0145	-8.4601	0.7352	0.066	0.069	0.003
	-11878.61	1.4124	7.4341		0.0080	1.4959	0.4900	0.160	4.015	13.273
BELL	**Market**	0.8712	0.9954		-0.0074	-8.5371	-0.0384	0.1395	0.9415	0.0051
	-12479.42	0.0325	0.0055		0.0023	0.1967	0.0060	0.0084	0.0100	0.0014
NORDSTROM	**Market**	1.5057	0.9953		-0.0124	-7.5028	0.0023	0.0195	0.9955	0.0004
	-10256.28	0.0779	0.0078		0.0052	0.0760	0.0028	0.0026	0.0014	0.0001
TW	**Market**	1.1036	0.9167		-0.0541	-8.5110	0.0154	0.3183	0.6648	0.0006
	-11540.13	0.0260	0.0324		0.0113	0.3390	0.0106	0.0160	0.0274	0.0114
AT&T	**Market**	0.9713			-0.0520	-8.6431	0.8037	-0.0604	0.2516	0.0063
	-12598.40	0.0009			0.0012	0.0114	0.0518	0.0020	0.0191	0.0465

1. Standard errors are estimated using Newey-West heteroskedasticity estimator and appear below the coefficient estimates.
2. Log likelihood values are presented below the model specification.

<TABLE 5> DOUBLE BETA MODEL PARAMETER ESTIMATES (CONSTANT BETA MODEL)

$$\ln(\sigma_{i,t}^2) = \alpha_i + \delta_i \cdot [\ln(\sigma_{i,t-1}^2) - \alpha_i] + \theta_i \cdot z_{i,t-1} + \gamma_i [| z_{i,t-1} | - E| z_i |] + \delta_{i,m} \ln(\sigma_{m,t}^2)$$

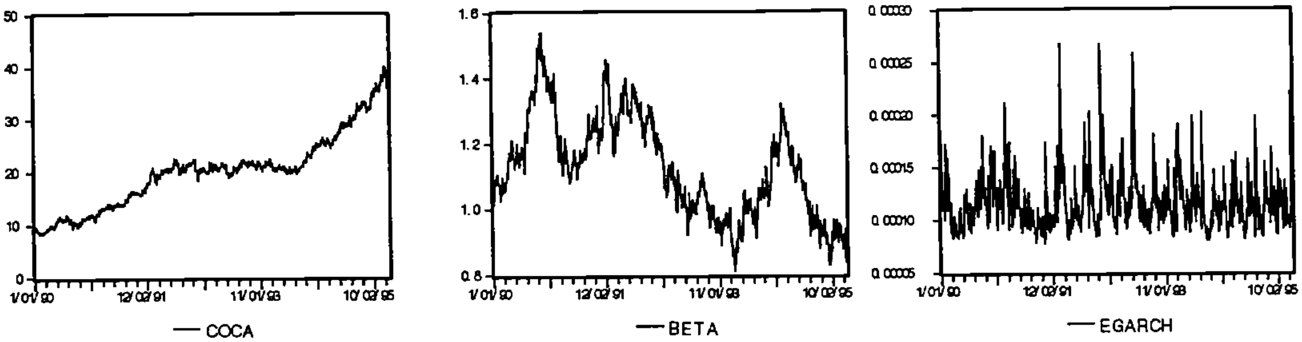
$$\beta_{i,t} = \alpha_\beta + \delta_\beta \cdot [\beta_{i,t-1} - \alpha_\beta] + \lambda_i \cdot z_{i,t-1} + \lambda_m \cdot z_{m,t-1}$$

Firm	Model	α_β	δ_β	λ_i	λ_m	α_i	δ_i	θ_i	γ_i	$\delta_{i,m}$
IBM	**Joint**	0.9013		0.1000	-0.0715	-6.9613	-0.0420	0.0664	0.9933	0.0004
	-11836.67	0.0013		0.0015	0.0010	0.0337	0.0006	0.0107	0.0292	0.0168
	Idiosyncratic	0.9745		0.0163		-7.6788	0.9043	-0.0390	0.1844	0.0119
	-12600.06	0.0037		0.0046		0.3547	0.0442	0.0020	0.0189	0.2982
	Market	0.9613			-0.0542	-7.6731	0.9054	-0.0401	0.1866	0.0118
	-12601.67	0.0070			0.0027	1.7178	0.9721	0.0146	0.3460	2.3585

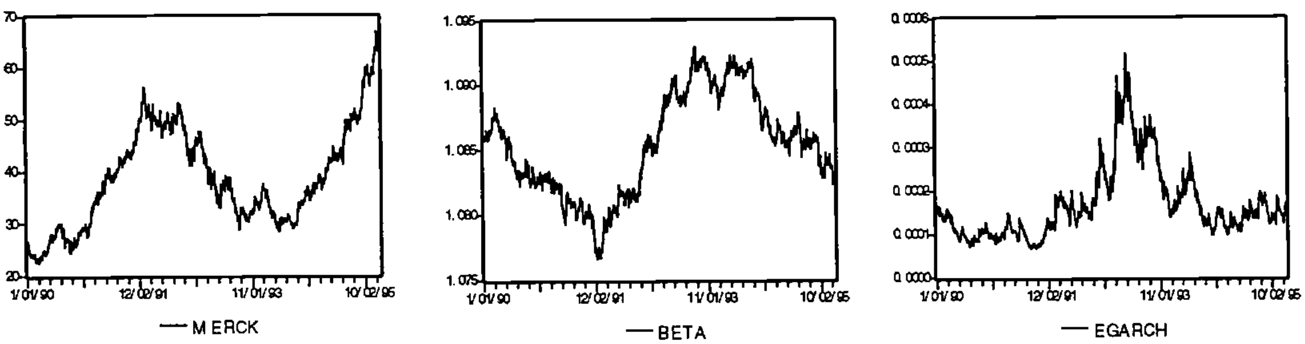
1. Standard errors are estimated using Newey-West heteroskedasticity estimator and appear below the coefficient estimates.

2. Log likelihood values are presented below the model specification.

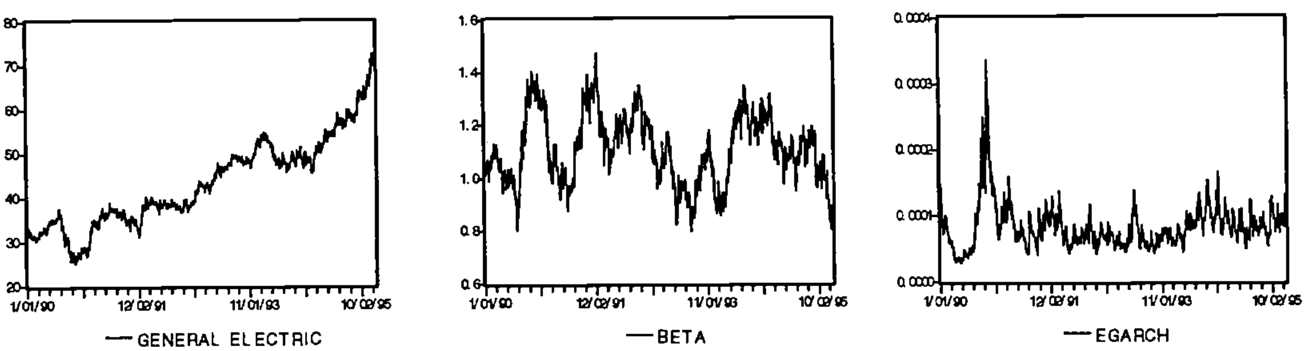
<FIGURE 1> COCA COLA



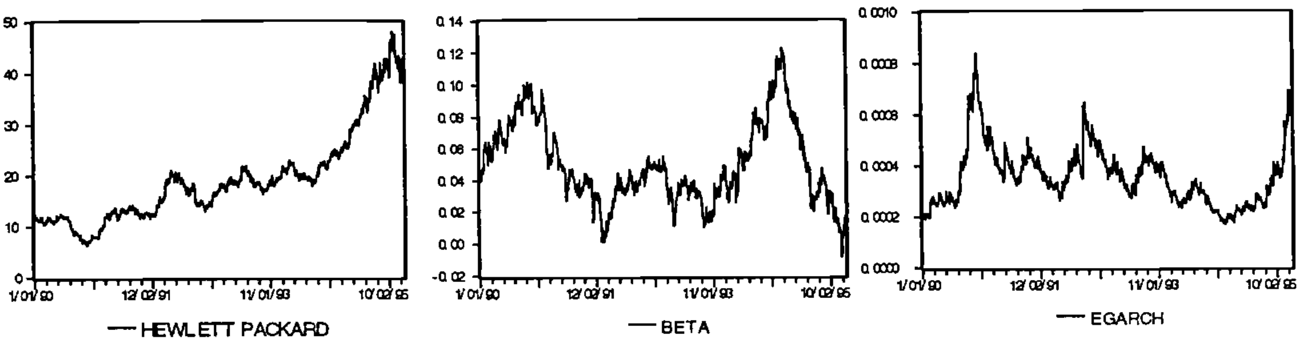
<FIGURE 2> MERCK



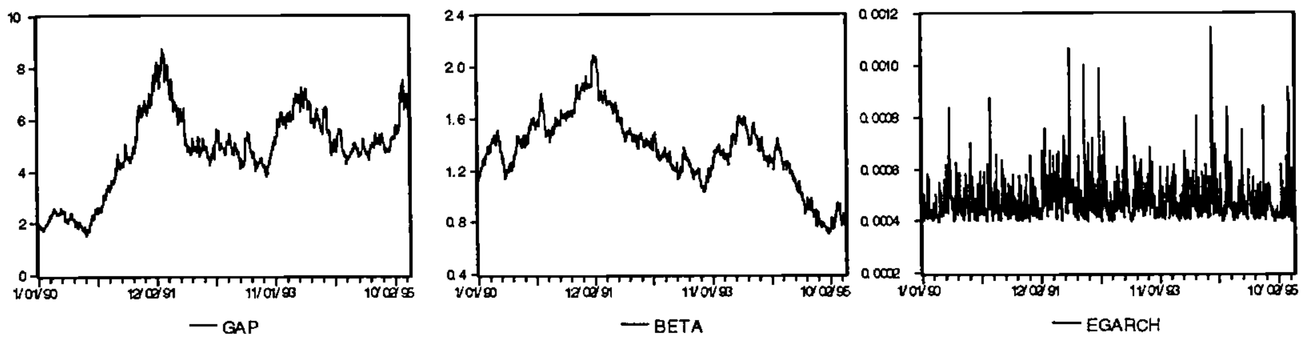
<FIGURE 3> GENERAL ELECTRIC



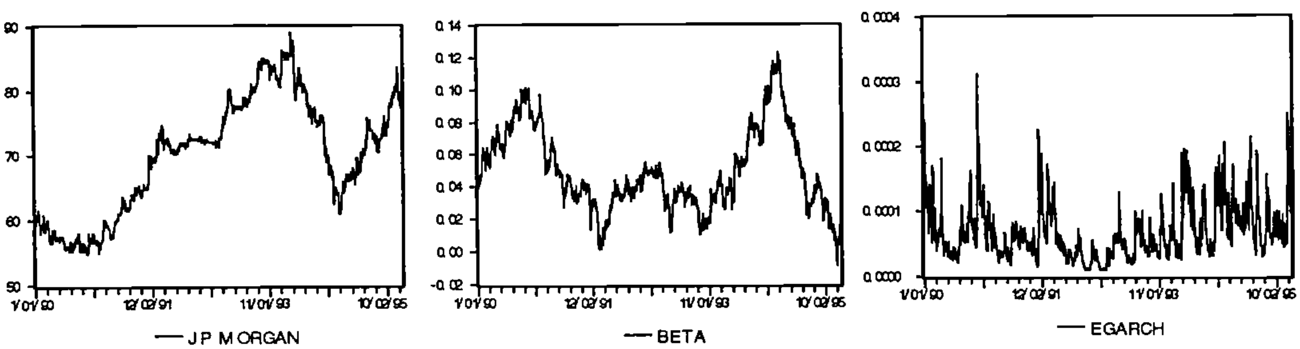
<FIGURE 7> HEWLETT PACKARD



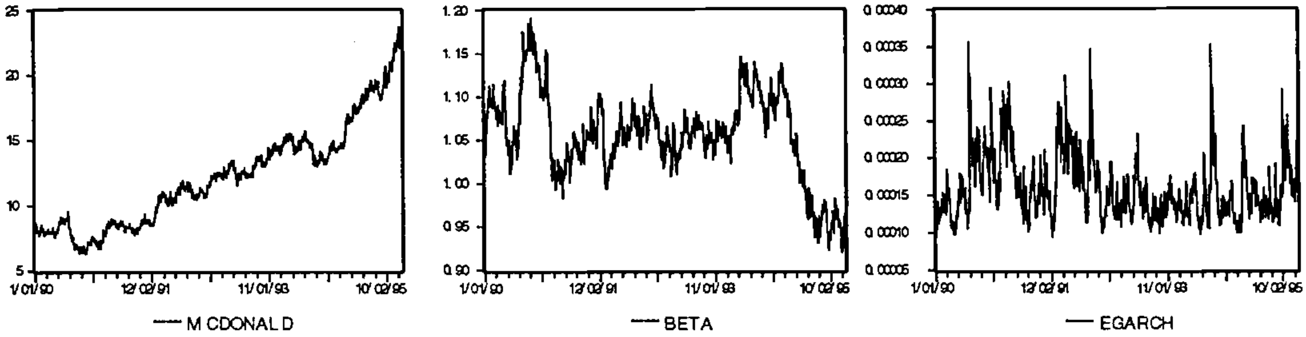
<FIGURE 8> GAP



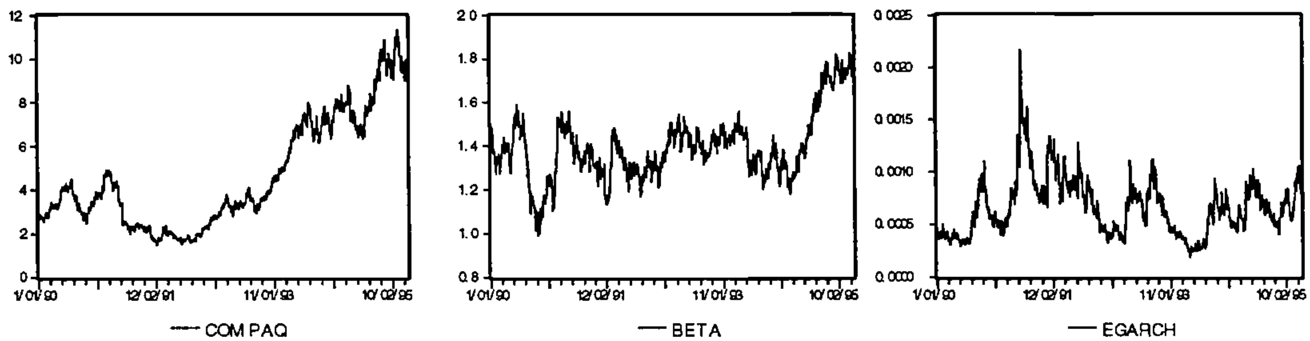
<FIGURE 9> JP MORGAN



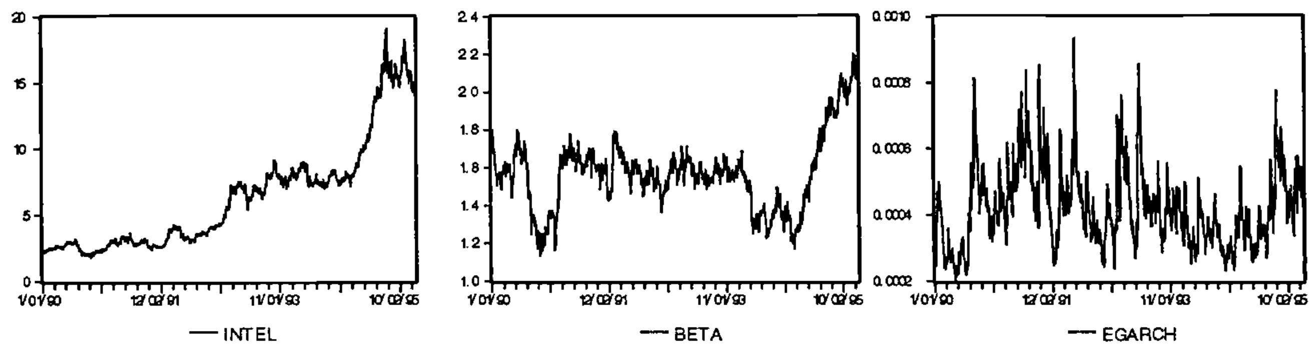
<FIGURE 10> MCDONALD



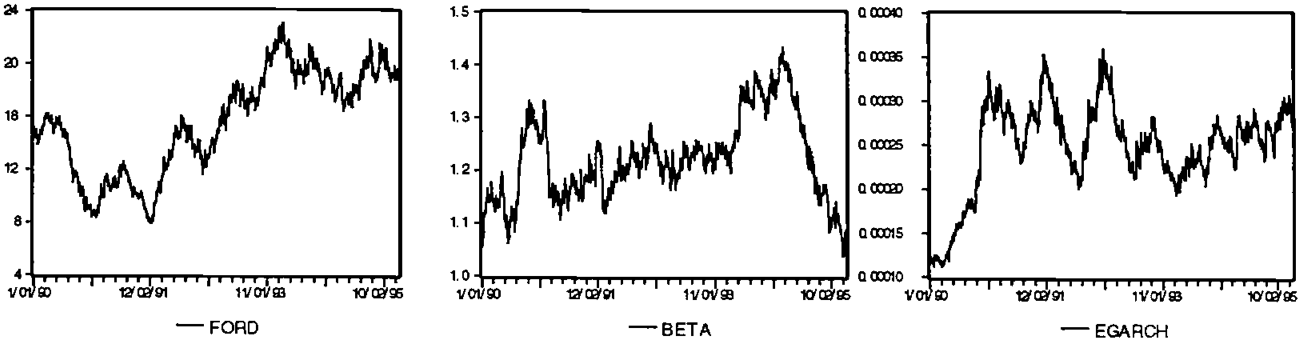
<FIGURE 11> COMPAQ



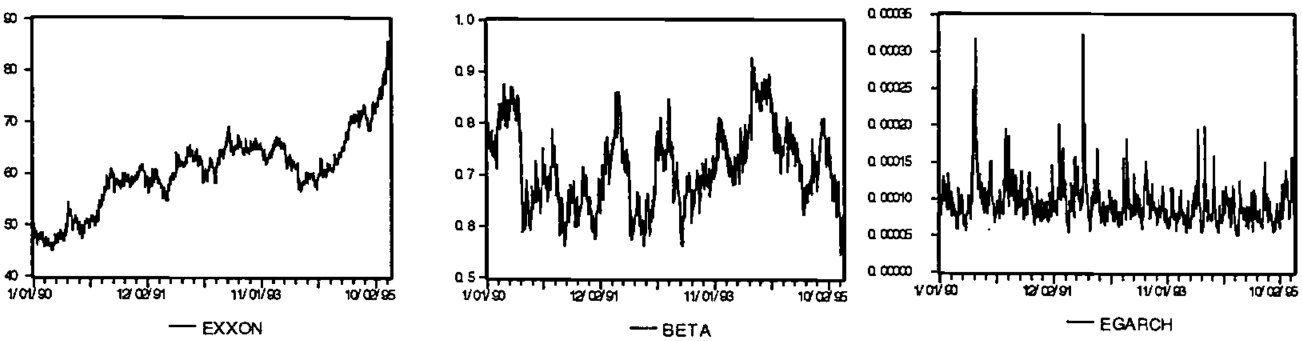
<FIGURE 12> INTEL



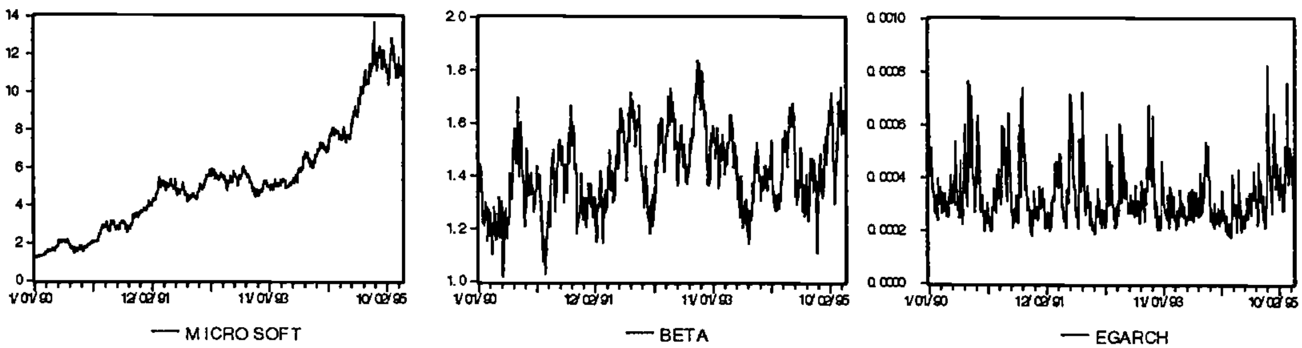
<FIGURE 13> FORD



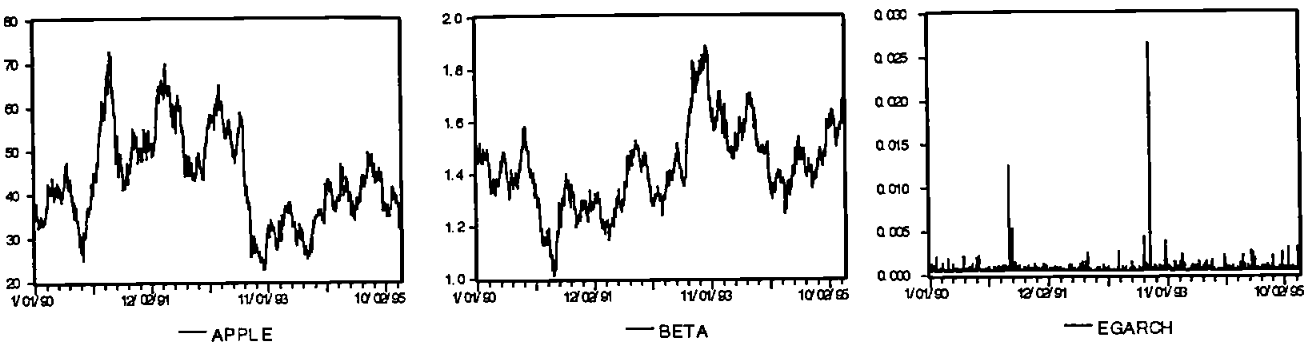
<FIGURE 14> EXXON



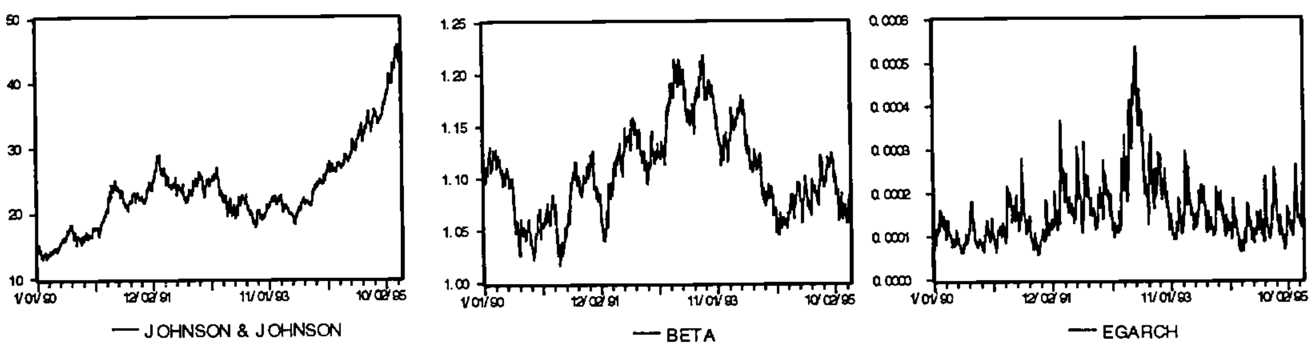
<FIGURE 15> MICRO SOFT



<FIGURE 16> APPLE



<FIGURE 17> JOHNSON & JOHNSON



<FIGURE 18> SUN