Nonlinearities And Volatility Patterns In Corporate Earnings

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Abstract

This paper explores the stochastic properties of the quarterly earnings per share series for industrials, railroads and utilities since 1935. Evidence of stochastic dependency suggests modeling them as a conditionally heteroskedastic process. Changes in earnings tentatively reject the random walk hypothesis since future returns can be predicted from past information. The conditional variance is found to be sensitive to market advances and positively correlated with the conditional mean since the risk premium is statistically significant. Finally, volatility persistence appears to be high in all series.

Introduction

An increasing interest in the volatility or the stochastic behavior of various financial data such as stocks, exchange rates, and precious metals has developed lately.[1] Until recently, the financial literature modeled volatility (or standard deviation) under the classical assumptions of constancy of variances and normality in the residuals. Subsequent research provided evidence for rejections of homoskedasticity and independence. As a result, a rich empirical body emerged to model volatility as a conditional heteroskedastic process, along with many parametric specifications that would be capable of accounting for higher-order dependencies.

Engle (1982) was first to introduce such a model, called Auto-Regressive Conditional Heteroskedastic (ARCH), in which the conditional variance is a linear function of its own lagged squared realizations. The model's later modification by Bollerslev (1986), the Generalized ARCH, proved to be successful in providing a parsimonious parameterization of second-moment dependencies. Since then a number of variants of this specification were developed to capture the nonlinearities in the data such as spillovers, persistence and asymmetric behavior of volatility.[2] Understanding the nature of processes that underlie the behavior of such series is important for the study of a number financial and economic issues like the pricing of derivatives such as futures and options, for which input of the future volatility is necessary. A similar argument can be made for the investigation of the stochastic behavior of corporate earnings since this has become a major goal in the accounting literature.[3] For instance, the layout of optimal expectation and the design of equity valuation and capital models are among the issues that crucially depend upon expected earnings growth.[4]

This paper explores the time-varying behavior of corporate earnings to determine whether future returns are predictable from past information (that is, test the random walk hypothesis) or there is evidence of any time dependency in the conditional variances and means of the series. Further, the issue whether positive

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or negative market shocks exert a similar or different impact on the volatility of the earnings, i.e., existence of asymmetric behavior, will be investigated. To empirically address these issues, the Asymmetric Power Auto-Regressive Conditional Heteroskedastic in-Mean (APARCH-M) model will be employed, which is capable of capturing potential asymmetries in the volatility structure of earnings.

In the rest of the paper, section II presents preliminary findings and describes the data, section III lays out the model specification and discusses the results, and, lastly section IV summarizes the major findings and concludes with some remarks.

Data And Preliminary Statistical Investigation

The data set is composed of the actual quarterly corporate earnings per share (adjusted to price index) obtained from the *Standard & Poor's* Security Price Index Record Statistical Service, based on stocks in the S&P's daily stock price indices. The series examined are the three major industry classifications, namely industrials, railroads, and utilities for the 1935:I to 1996:IV period.[5] We also included the Composite Earnings Per Share (CEPS) variable, which reflects an average of the series. All series are examined in real terms (the Consumer Price Index was used as a deflator). In Table 1, the results from the preliminary statistical investigation of the series are exhibited. To gain first insights about the series we need to test for stationarity. For that purpose, the Augmented Dickey-Fuller and the Phillips-Perron tests are used.[6] The series were transformed in their first differences so as to become stationary. This is determined by noting that the calculated values of the above statistics are above the corresponding sample critical values. Additional preliminary findings (not reported here), from a graphical inspection of the series' trends, imply that the series were subject to some structural change at some point in time. Specifically, the industrials showed a significant upward drift and increased volatility after 1946, whereas the utilities, being roughly stable until 1946, started drifting upwards thereafter. Finally, the railroads exhibit a significant degree of volatility especially pronounced after 1982 where industry deregulation took place. Thus, it is suggested that both variance and mean effects are present in the data except for the utilities. The first effect is implied by the significance of the means in all (sub)periods for the series and the second effect indicates heteroskedasticity, as variance sharply changed in the second period, thus reflecting the above-noted volatility.

The empirical distributions of the series are slightly negatively skewed with fatter tails, compared to the normal distribution. This pattern, or contemporaneous asymmetry, implies that large negative earnings changes are more common than large positive ones. Moreover, extreme market movements are more usual than expected, if a normal distribution were to describe them, hence the existence of excess kurtosis. Further insights about departures from normality in the series are gained from the Kolmogorov-Smirnov D-statistic for normality check, the Ljung-Box and the Lagrangian Multiplier statistics for conditional heteroskedasticity. The D-statistic validates this result by rejecting normality in the series at the five percent level. Finally, the LB values suggest time dependencies at four and eight lags and become stronger, as the squared LB values imply, that is, there is evidence of existence of significant higher-order time dependencies. Thus, it is concluded that the percentage changes in the series exhibit notable first- and second-order nonlinearities.

Model Specification And Results

Methodology

One of the most interesting results of the recent literature is the conclusion that such distinct deviations of financial data from the traditional assumptions can be adequately represented by a low order GARCH(1,1). In this paper we will employ Ding's *et al.* (1993) Asymmetric Power Auto-Regressive Conditional Heteroskedastic in-Mean (APARCH-M) model to explain volatility patterns in corporate earnings.[7] The generality feature of this version allows for several nested ARCH-type models so as to determine the appropriate one for each series. This specification also remedies the problem found in traditional GARCH-type models, which assume that past shocks exert the same impact on volatility irrespective of their nature. Recent evidence documents such asymmetric behavior, or that unanticipated negative shocks have a different impact on volatility than do unanticipated positive shocks. The model then can be expressed as follows:

$$R_t | \Omega_{t-1} \sim N\{\mu_t, \sigma_t\} \quad (1)$$

$$\mu_t = b_0 + b_2 (\sigma_{t|t-1}) \quad (2)$$

$$\sigma^{\delta}_t = \alpha_0 + \sum_{i=1}^{p} \alpha_1 \{ |\varepsilon_{t-1}| - \gamma (\varepsilon_{t-1}) \}^{\delta} + \sum_{i=1}^{q} \beta (\sigma^{\delta}_{t-1})\}$$

$$\text{where } -1 < \gamma < 1 \quad \text{and } \delta \geq 0 \quad (3)$$

$$\text{LogL} = -(1/2)\{\log(\sigma_t) + \varepsilon^2_t/\sigma^2_t\} \quad (4)$$

Equation (1) describes the conditional probability density function of, R_t, as normal with μ_t and σ_t as the conditional mean and the conditional standard deviation, respectively, based on the information set Ω_{t-1}. The conditional mean (equation 2) is specified as a function of the conditional standard deviation, or the ARCH-M effect, which, if significant, implies that current information can be used to predict future changes in the series. The conditional variance (equation 3) is expressed as a Box-Cox transformation on the (asymmetric) function of past innovations (the terms in the brackets) and on its past conditional standard deviation (the error terms are defined as $\varepsilon_t = R_t - \mu_t$). The absolute error terms represent the impact of a shock regardless of its sign, while $\gamma\varepsilon_{t-1}$ represents the sign effect. For example, if $\gamma > 0$ then negative shocks increase volatility by more than positive shocks (of equal magnitude), i.e., evidence of asymmetric behavior. Thus, this formulation permits us to investigate the differing impact of market shocks (advances or declines) on the volatility of the earnings series.

Basically, this restriction (δ) is the familiar constant elasticity of substitution, usually imposed on the traditional production functions, and its value should give us a clue about the specification of the innovations in the conditional variance of the series. This amounts to saying that it should be left up to the data to determine the optimal definition of volatility for each time series. The final term in equation 3, β (along with α_1), measure(s) the persistence of volatility and if their sum is less than one then the conditional variance is stationary. Lastly, equation 4 describes the sample likelihood function of the returns.

Empirical Results

Table 2 (panel A) reports the maximum likelihood estimates of the parameters of equations 2 and 3. The optimal lag lengths for the conditional mean and variance were determined using the Schwarz Information Criterion (SIC), where the objective is to minimize its value.[8] A p=q=1 GARCH specification was found to adequately represent the conditional variance, a result expected given the fact that many studies have documented this. Likelihood ratio tests designed to test the joint significance of the coefficients (α=β=γ=0) rejected the null hypothesis at the five percent level. Turning our attention to the results, we see that the coefficients, b_2, linking the conditional mean with the conditional standard deviation (the ARCH-M effects), are positive and highly significant for all series. In theory, this characteristic can be exploited to predict future movements in the returns since the only input is past innovations and past volatility (as specified here). This may contradict the random walk hypothesis, according to which future values are not predictable from past information.[9] Earlier studies on this issue employing

TABLE 1
Preliminary Statistics

	CEPS	Industrials	Railroads	Utilities
1st Period	(1935:I-1946:I)	(1935:I-1946:I)	(1935:I-1982:I)	(1935:I-1946:I)
mean	-0.0555	-1.5845*	-0.3420*	-1.2241
variance	0.0429	0.0981	0.3981	0.0838
skewness	-0.6280	-0.4644	-0.8010	0.1558
kurtosis	0.8254	0.2988	1.4434	-0.2923
2nd Period	(1935:I-1946:I)	(1935:I-1946:I)	(1935:I-1982:I)	(1935:I-1946:I)
mean	1.8711*	0.5413*	0.6589*	0.0686
variance	0.5928	0.6183	1.5415	0.4725
skewness	0.0819	0.1069	-1.9011*	-0.2622
kurtosis	-1.2401	-1.2217	3.9640*	-0.9166
Entire Period (1935:I-1996:IV)				
ADF	-8.4162	-8.3370	-9.0098	-8.3785
P-P	-23.7889	-22.4567	-29.0312	-29.8721
Mean	1.4578*	1.3971	0.5459	0.7744
St. Deviat.	11.0785	20.2577	30.8289	32.6699
Skewness	-0.9172*	0.2572*	-0.3351*	-0.0578
Kurtosis	-1.0888*	4.3208*	10.5225*	-1.2122
D-stat	0.1618*	0.1758*	0.2231*	0.4070*
L-M	4.8910	7.1913**	26.7890*	12.1925**
LB(4)	67.9972*	56.0327*	51.1882*	462.8901*
LB(8)	123.5510*	112.3126*	90.5721*	851.8891*
$LB^2(4)$	89.7889*	131.3678*	105.6611*	1197.7881*
$LB^2(8)$	98.2111*	150.3211*	198.9010*	1200.2111*

Notes: * statistically significant at the 5 percent level; ** at the 10% level; CEPS is the actual Composite Earnings Per Share; the critical values for the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (P-P) tests are -3.4407, -2.8661, and -2.5692 for the 1%, 5%, and 10% levels of significance, respectively; the D-stat is the Kolmogorov-Smirnov statistic for normality check and its critical value is 0.1102 (calculated as 1.36//n=240) at the 5% level; the L-M statistic is the Lagrangian Multiplier; the LB(n) and $LB^2(n)$ statistics for regular and squared series, respectively, refer to the Ljung-Box statistic for testing for presence of time dependencies for the *n*th lag, and follow a χ^2 distribution with n degrees of freedom.

various approaches ranging from first- and higher-order autocorrelations [Albrecht, Lookabill, and McKeown, 1977, Watts and Leftwich, 1977, Ohlson, 1991, and Lipe and Kormendi, 1993] to more sophisticated techniques such as the Maximum Entropy Method [Callen, Cheung, Kwan, and Yip, 1994] and firm-specific models [Finger, 1994] provided mixed results.

Regarding the conditional variance equation results, we see that the coefficient of

TABLE 2
Maximum Likelihood Estimates And Standardized Residual Diagnostics of the APARCH-M Model

PANEL A ML Estimates

Series	b_0	b_2	α_0	α_1	β	γ	δ	logL
CEPS	0.0332*	0.3546*	-2.7416*	0.0111*	0.9683*	0.3164*	0.4326	-287.890
	(0.010)	(0.067)	(0.254)	(0.987)	(0.766)	(0.103)	(0.311)	
INDU	-8.4844*	1.6879*	1.4423*	-0.6191	0.8686*	1.1063	1.9871*	-762.988
	(1.778)	(0.566)	(0.700)	(0.987)	(0.154)	(0.670)	(2.233)	
RAIL	-13.8911*	-3.2131*	1.1034*	0.4019*	0.1778*	1.0691*	0.8468*	-987.829
	(1.789)	(0.112)	(0.324)	(0.652)	(0.030)	(0.007)	(0.034)	
UTIL	0.2644	0.2077*	0.0477	-0.3078	1.0001	0.4432	0.7272*	-162.212
	(0.200)	(0.102)	(0.028)	(0.789)	(0.511)	(0.231)	(0.308)	

PANEL B Residual Diagnostics

	CEPS	**INDUSTRIALS**	**RAILROADS**	**UTILITIES**
Mean	-0.0341	0.0911	-0.0031	0.0321
Variance	1.0000	1.0040	1.0011	1.0019
Skewness	-0.5228	-0.0867	-2.9891*	1.1435*
Kurtosis	1.4738	0.2976	2.7891	0.1451
LB(4)	10.7221	58.9010*	12.6678	123.7789*
LB(8)	19.7789	114.7889*	19.6372	145.7781*
$LB^2(4)$	44.7781*	11.5426	0.3256	567.8901*
$LB^2(8)$	98.7889*	19.0019	0.3321	654.1451*
D-stat	0.0987	0.1042	0.1101	0.1435*
L-M	5.8789	6.8890	2.8910	32.8991*

Notes: Panel A: CEPS is the earnings per share composite; INDU is the industrials; RAIL the railroads; UTIL the utilities; * denotes significance at the 5 percent level; standard errors in parentheses; sample period is from 1935:2 to 1996:4, for a total of 244 observations; LogL is the log-likelihood function.

Panel B: the results pertain to the standardized residuals; D-stat is the Kolmogorov-Smirnov test statistic for normality and the sample critical value at the 5% level is 0.1102; the LB(n) and $LB^2(n)$ are the *nth* lag Ljung-Box statistics for the regular and the squared series, respectively, and follow χ^2 with n degrees of freedom.

past innovations, α_1, corresponding to the asymmetric function is positive and significant for the composite and the railroads series. This allows us to conclude that past standardized residuals influence current volatility. Also, the past conditional variance or the volatility persistence coefficient, β, is positive and highly significant for the railroads and industrials. To calculate the persistence of past shocks to volatility, we use the Half-Life of a shock computed as $HL = [(\ln(0.5)/\ln(\beta)]$ or 1.4 for the utilities and 2.0 for the railroads, which means that persistence lasts approximately one and a half quarter for the utilities and just two quarters for the railroads. Interestingly, the significance of the positive coefficient suggests that positive shocks increase volatility more than negative shocks of an equal magnitude. This could be taken to mean that investors' regard market advances as simply speculative bubbles, especially when the economic fundamentals are not present, among other things, thus feeding a stream of uncertainty during such periods. These characteristics can also be explained by the so-called 'volatility-feedback' phenomenon, put forth by Pindyck (1984) and French, Schwert and Stambaugh (1987). In principle, large pieces of good news tend to be followed by another batch of good news (volatility persistence) and so future volatility increases. Hence, volatility feedback implies that the earnings movements are correlated with future volatility.

The estimate of δ provides an idea of the degree of (non)linearity in the conditional variance. For instance, modeling the conditional variance of the industrials with a $\delta = 2$, would appear to be a reasonable assumption since the coefficient is not statistically different from two, while for the railroads and the utilities an asymmetric GARCH for the standard deviation would have been preferable given that δ is not statistically different from one.

Panel B of Table 2 reports the results from the diagnostic tests performed on the standardized residuals. Correct model specification requires that the residuals have mean zero and unitary variance. The results confirming time-varying behavior, however, reveal mixed evidence. Specifically, linear independence is exhibited by the composite earnings and the railroads series but not by the industrials and the utilities. Further, nonlinear independence is rejected for the composite and the utilities series as the LB statistics for the squared residuals are significant. The D-statistics for normality check indicate its presence in all but the utilities series, as do the Lagrangian Multiplier (LM) values. Lastly, the skewness and kurtosis measures are smaller and insignificant than the raw data, which constitute a final check for the appropriateness of the APARCH-M specification to explain the time dependencies observed in the earnings series.

IV. Summary And Conclusions

The paper explores the stochastic properties of the earnings series from 1935:I to 1996:IV. Preliminary data investigation reveals linear and nonlinear time dependencies in the series, which suggest modeling them as a conditionally heteroskedastic process. Changes in earnings reject the random walk hypothesis and thus future returns can be predictable from past information. The conditional variance is a function of past standardized residuals and past (conditional) variances and sensitive to market advances. Moreover, volatility persistence is high in these markets. There is also evidence that the conditional standard deviation is positively correlated with the conditional mean since the risk premium is significant. Finally, standardized residual diagnostics generally support a correct APARCH-M model specification, given that the model accounts for most of the time dependencies inherent in the series.

Suggestions for further research

Some recommendations for further research would include the examination of the impact of corporate announcements such as dividends on the volatility of earnings using other variants of the GARCH-type models. Moreover, the investigation of the persistence and predictability of one-period returns and their effects on the volatility of stock prices could be worthwhile. 🕮

The author wishes to thank an anonymous referee and Professor Noronha (editor) for many valuable comments that greatly improved the paper. Any errors, naturally, remain my responsibility.

Endnotes

1. See for instance Baillie and Bollerslev (1990), Akgiray *et al.* (1991), and Koutmos (1992,1993).
2. See Susmel and Engle (1994) and Laopodis (1996, 1998).
3. Lev (1983), Cheung and Li (1994) to name a few.
4. Lev (1983).
5. According to the data source, since 1935 earnings data was based only on companies that reported quarterly earnings. Beginning with the fourth quarter of 1950, estimates of earnings for the missing companies were used in order to maintain consistent coverage. Rail earnings have been revised since 1967 to reflect consolidated earnings.
6. The Augmented Dickey-Fuller (ADF) test involves estimating the following model:

$$R_t = a_0 + a_1 t + a_2 R_{t-1} + \sum_{s=1}^{k} c_s w_{t-s} + u_t$$

and testing the null H_0: $a_2 = 0$ versus the alternative H_a: $a_2 < 0$, where $R_t = \log(R_t)$, $w_t = R_t - R_{t-1}$, and t is a trend variable. See Dickey and Fuller (1981). The Phillips-Perron (P-P) test is done by means of estimating the following model:

$$R_t = b_0 + b_1 (t - T/2) + b_2 R_{t-1} + v_t$$

and testing the null H_0: $b_2 = 1$ versus the alternative H_a: $b_2 < 1$, where T is the sample size. See Phillips and Perron (1988) for details. Acceptance of the H_0 implies presence of a unit root in the R_t series.

7. Some applications of this model are those by Koutmos (1993), to model the behavior of several U.S. dollar exchange rate volatilities during appreciations and depreciations, and by Fornari and Mele (1997), to explain business cycles asymmetry.
8. Its specification is as follows: SIC = -(maxLogl-(1/2)K log(T)/T), where maxLogl is the sample log-likelihood function evaluated at maximum, K the number of estimated parameters, and T the number of observations.
9. This is a tentative result since the sample size interval is quarterly. This result may have not occurred if the data were weekly or daily.

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