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Conditional and Unconditional Heteroscedasticity
in the Market Model

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Abstract

Unlike previous studies, this paper tests for both conditional and unconditional heteroscedasticities in the market model, and attempts to provide an alternative estimation of betas based on the autoregressive conditional heteroscedastic (ARCH) model introduced by Engle. Using the monthly stock rate of return data secured from the CRSP tape for the period of 1976-1983, it is shown that conditional heteroscedasticity is more widespread than unconditional heteroscedasticity, suggesting the necessity of the model refinements taking the conditional heteroscedasticity into account. In addition, the efficiency of the market model coefficients is markedly improved across all firms in the sample through the ARCH technique.

Conditional and Unconditional Heteroscedasticity in the Market Model

I. Introduction

Over the past two decades, the capital asset pricing model (CAPM) has been more widely used in finance than any other model. Inherent in the CAPM is that capital assets, under some simple assumptions, are held as functions of the expected means and variances of the rates of return, and that investors pay only for the systematic risks of capital assets which are measured by the relationship between the return on individual assets and the return on the market (e.g., the single-index market model of Sharpe [14]). However, a number of studies have raised questions on the validity of the market model to estimate the systematic risk of financial assets using the ordinary least squares (OLS) technique. In particular, a significant portion of the previous studies have focused on the variance structure of the market model (see for example [1], [2], [4], [5], [6], [8], [9], [12] and [13]).

In the traditional approach, when the mean is assumed to follow a standard linear regression, the variance is constrained to be constant over time. However, many studies have provided strong evidence of heteroscedasticity for a number of common stocks not only in the U.S. market but in the Canadian and European markets and attributed in general to model misspecification either by omitted variables or through structural changes. Giaccotto and Ali [10] used two classes of optimal nonparametric distribution-free tests for heteroscedasticity and applied them to the market model. They found the assumption of homoscedasticity to be untenable for the majority of stocks analyzed.

Lehmann and Warga [11] took issue with Giacotto and Ali's use of recursive residuals in rank tests in order to provide some information concerning the stochastic properties of market model regressions.

Nevertheless, most of the previous studies have been limited to investigating the existence of heteroscedasticity in the market model using different statistical tests and rarely considered estimation of betas taking heteroscedasticity explicitly into account. Furthermore, they considered only unconditional variances of the disturbance term, ignoring the possible changes in conditional variances. Some studies attempted to find a form of heteroscedasticity in an ad-hoc fashion. The predominant approach was to introduce an exogeneous variable (the market return in most cases) which may predict the variance. As pointed out by Engle [7], this conventional solution to the problem requires a specification of the causes of the changing variance in an ad-hoc fashion rather than recognizing that both means and variances conditional on the information available may jointly evolve over time.

The purpose of this study is to test for both conditional and unconditional heteroscedasticities, and provide an alternative estimation of betas based on the autoregressive conditional heteroscedastic (ARCH hereafter) model, introduced by Engle [7]. The ARCH process is characterized by mean zero, serially uncorrelated processes with non-constant variances conditional on the past but constant unconditional variances. This study is different from the earlier ones in some important aspects. First, using the ARCH model, this study provides a more realistic measure of betas when the underlying conditional variance may change over time and is predicted by the past forecast errors rather than making conventional assumptions about the disturbances. Second, it provides more efficient estimators using the maximum likelihood method. Third, it does not employ an arbitrary exogenous variable such as the market return to explain heteroscedasticity. Lastly, by the nature of the ARCH process, the effects of omitted variables from the estimated model, and a portion of non-normality of the regression disturbance terms, may be picked up.

Section II describes the model and section III presents empirical results. Section IV contains a brief summary.

II. Model

Consider the single index market model

$$\tilde{R}_{it} = \alpha_i + \beta_i \tilde{R}_{mt} + \tilde{E}_{it} \tag{1}$$

where $\tilde{R}_{it}$ and $\tilde{R}_{mt}$ are the random return on security i and the random market return, respectively, in period t; α_i and β_i are the regression parameters of security i; $\tilde{E}_{it}$ is the random disturbance term with $E(\tilde{E}_{it}) = 0$ for all i and t. The parameter β_i measures the systematic risk of security i and is defined as $\mathrm{Cov}(\tilde{R}_i, \tilde{R}_m)/\mathrm{Var}(\tilde{R}_m)$. One of the many assumptions that model (1) is based on is that the disturbances are homoscedastic.

First, we check for unconditional heteroscedasticity using the White [15] test which does not assume any specific form of the heteroscedasticity. Second, we test for conditional heteroscedasticity and simultaneously attempt to reestimate the market model with an ARCH specification.

For ease of exposition, let us put model (1) in a general linear regression framework in matrix notation:

$$\underset{(T\times 1)}{Y} = \underset{(T\times k)}{X}\ \underset{(k\times 1)}{\beta} + \underset{(T\times 1)}{E} \tag{2}$$

with k=2. Let $\hat{\beta}$ be the OLS estimator. If the E's are homoscedastic, then a consistent estimator of the variance-covariance matrix of $\hat{\beta}$ is given by

$$\hat{V}_1(\hat{\beta}) = \hat{\sigma}^2(X'X)^{-1} \tag{3}$$

where $\hat{\sigma}^2 = \hat{E}'\hat{E}/T-k$ and $\hat{E}$'s are the OLS residuals.

In the presence of heteroscedescity, a consistent estimator of $\hat{\beta}$ will be

$$\hat{V}_2(\hat{\beta}) = (X'X)^{-1}(X'\hat{\Sigma}X)(X'X)^{-1} \tag{4}$$

where $\Sigma = \text{diag}\ (\hat{E}_1^2, \hat{E}_2^2, \ldots, \hat{E}_T^2)$.

Under homosecdasticity, these two estimates $\hat{V}_1(\hat{\beta})$ and $\hat{V}_2(\hat{\beta})$, will converge to the same limit. However, in case of possible heteroscedasticity, $\hat{V}_1(\hat{\beta})$ is inconsistent and these two estimators will have different limits. White's procedure is based on examining the statistical significance of the limits of the k(k+1)/2 distinct elements of the matrix $\hat{V} = \hat{V}_1(\hat{\beta}) - \hat{V}_2(\hat{\beta})$. Under the assumption of homoscedasticity, the test statistic is asymptotically distributed as χ^2 with k(k+1)/2 degrees of freedom. One attractive feature of this test is that it does not depend on a specific form of heteroscedasticity. Assuming that the disturbances are homokurtic, the test statistic can be calculated as $T \cdot R^2$ where R^2 is the coefficient of determination obtained by regressing the square of the residuals on a constant, $\tilde{R}_{mt}$ and $\tilde{R}^2_{mt}$. The test statistic will have 2 degrees of freedom (one less because of the presence of an intercept term in the regression).

Following Engle [7], we assume that the conditional heteroscedasticity of the market model can be represented by a first-order ARCH process (suppressing the suffix i) as:

$$V(E_t/E_{t-1}) = \sigma_t^2 = \gamma_0 + \gamma_1 E_{t-1}^2 , \tag{5}$$

where $\gamma_0 > 0$, and $0 \leq \gamma_1 < 1$.

This type of conditional heteroscedasticity has some intuitive appeal since it does not depend on some arbitrary exogenous variables and can be viewed as some average of the square of the past disturbances. When $\gamma_1 = 0$, we have conditional homoscedasticity. It can be easily shown that unconditionally $E(E_t) = 0$, $V(E_t) = \gamma_o/(1-\gamma_1)$ and $E(E_t E_{t'}) = 0$ for $t \neq t'$ (see Engle [7] for details). Since we do not have any lagged dependent variable in our model, $\hat{V}_1(\hat{\beta}) - \hat{V}_2(\hat{\beta})$ will have the same probability limit. Therefore, White's procedure will test only for unconditional heteroscedasticity, while the test for $\gamma_1 = 0$ in (5) will provide a test for conditional heteroscedasticity. It is also important to note that under the ARCH model, the E_t's are uncorrelated but dependent, which is a property of non-normal distributions.

The log-likelihood function assuming normality is given by

$$L = \sum_{t=1}^{T} (a - \frac{1}{2} \log \sigma_t^2 - \frac{1}{2} E_t^2/\sigma_t^2) \tag{6}$$

where a is a constant term and $E_t = \tilde{R}_t - \alpha - \beta \tilde{R}_{mt}$. Using Quandt's subroutine GRADX of his numerical optimization program GQOPT3, we maximize the function L and obtain estimates of α, β, γ_0 and γ_1. These estimates of α and β are compared with the OLS estimates. Significance of γ_1 will indicate the presence of conditional heteroscedasticity. This is tested using t-statistics.

We also test for normality of the disturbances of the OLS and ARCH models. The test statistic is calculated as:

$$T\left[\frac{(\text{skewness})^2}{6} + \frac{(\text{kurtosis}-3)^2}{24}\right].$$

Under normality this test statistic asymptotically follows a central χ^2 with 2 degrees of freedom (see Bera and Jarque [3] for details).

III. Empirical Results

Monthly stock rate of return data was secured from the CRSP tapes for the period 1976-83 (96 months) for 35 randomly chosen firms without missing values. Market model regressions using the OLS and ARCH methods were run for each firm. The homoscedasticity and normality tests statistics also were calculated. The results based on the OLS regression and the ARCH model are shown in Tables 1 and 2, respectively.

First, from the results on the White test we can observe that only for ten firms the test statistics are significant at 1% and 5% levels. This indicates that the unconditional heteroscedasticity may not be very important. However, all of the normality test statistics are significant indicating the presence of strong non-normality. The OLS results exhibit the familiar strong significance of the beta coefficient, with 33 of the market models having beta t-values significant at the 1% level. The intercept $\hat{\alpha}$ terms are, for the most part, small and insignificant.

The importance of conditional heteroscedasticity and thus the appropriateness of the ARCH model can be judged from the significance of 26 γ_1 values in Table 2. It should be noted, however, that the significance of γ_1 (a test of conditional heteroscedasticity) in Table 2 has no relation with the earlier test for unconditional heteroscedasticity in Table 1. This is not surprising since they test two completely different hypotheses. For the ARCH model also, the 33 betas are significant and the significance of several of the intercepts is enhanced. Of particular interest is the change in beta as a result of the use of ARCH. Fourteen of the 33 firms with significant OLS betas have increased betas when ARCH is used; nineteen others have beta reductions. However, most of the changes are small. Nineteen ARCH model betas change no more than 4 percent up or down from their OLS counterparts. Six firms' betas increase by 5% or more when ARCH is used, while eight betas decrease by at least 5%. Only five firms (14.3% of the sample) have betas change by 10% or more.

The efficiency of the market model coefficients is markedly improved across all firms. The t-values for all the ARCH model betas are higher than those for the OLS model due to the lower standard errors of the coefficients. Thus it appears that incorporation of a conditional heteroscedastic component results in greater efficiency, though affecting the parameter estimates themselves slightly. In sum, the differences between the OLS and ARCH results reveal the importance of taking account of conditional heteroscedasticity in the market model.

Lastly, the results on normality tests indicate strong non-normality of the disturbance terms in the ARCH model. This is what we should expect because, as pointed out earlier, the ARCH errors are inherently non-normal or mutually dependent. The ARCH procedure takes account of this type of non-normality or the dependent structure, while the OLS procedure (results of Table 1) neglects it. The gain is reflected in the improved standard errors of $\hat{\alpha}$ and $\hat{\beta}$ in Table 2.

IV. Summary

A number of studies have shown that heteroscedasticity in the market model is widespread. However, the previous studies have been limited to investigating the existence of heteroscedasticity using different statistical tests and rarely considered estimation of betas taking heteroscedasticity explicitly into account. Furthermore, they considered only unconditional heteroscedasticity, ignoring conditional heteroscedasticity. This paper tests for both conditional and unconditional heteroscedasticities and provides an alternative estimation of betas based on the autoregressive conditional heteroscedastic (ARCH) model introduced by Engle. Using the monthly stock rate of return data secured from the CRSP tape for the period of 1976-1983, it is shown that conditional heteroscedasticity is more widespread than unconditional heteroscedasticity, suggesting the necessity of the model refinements taking the conditional heteroscedasticity into account. In addition, the efficiency of the market model coefficients is markedly improved across all firms in the sample through the ARCH technique.

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Table 1

Results Based on the Ordinary Least Squares Regression
(t-statistics are in parentheses)

Firm No.	$\hat{\alpha}$	$\hat{\beta}$	Homoscedasticity* (White test)	Normality*
1	-.002	1.22[a]	0.634	36.33[a]
	(-.026)	(7.70)		
2	.003	1.06[a]	3.005	22.40[a]
	(0.29)	(4.82)		
3	-.003	1.02[a]	1.152	19.29[a]
	(-0.66)	(8.72)		
4	.008[b]	0.69[a]	3.562	21.03[a]
	(2.10)	(8.35)		
5	.002	1.75[a]	8.774[b]	14.72[a]
	(0.18)	(6.72)		
6	.021b	0.07	0.115	14.47[a]
	(1.71)	(0.24)		
7	.009	-0.14	8.304[b]	22.72[a]
	(1.02)	(-0.69)		
8	.012	0.75[a]	9.053[b]	33.81[a]
	(1.58)	(4.44)		
9	.021	1.73[a]	0.557	20.79[a]
	(1.43)	(5.31)		
10	.002	1.02[a]	2.803	23.75[a]
	(0.33)	(6.81)		
11	-.001	1.05[a]	16.435[a]	21.08[a]
	(-0.15)	(7.32)		
12	.015	1.87[a]	0.701	9.05[b]
	(1.64)	(8.86)		
13	.010	0.99[a]	6.682[b]	42.68[a]
	(1.34)	(5.88)		
14	.002	1.07[a]	1.123	16.31[a]
	(0.23)	(6.95)		
15	.010	1.28[a]	4.848	20.39[a]
	(1.03)	(5.69)		
16	.016	0.77[a]	2.131	33.26[a]
	(1.38)	(3.04)		
17	-.006	1.26[a]	10.589[a]	47.57[a]
	(-0.85)	(8.36)		

*χ^2 test statistics.

[a]Significant at the 1% level; the critical value for t-statistics = 2.37 and the critical value for χ^2 statistics = 9.21.

[b]Significant at the 5% level; the critical value for t-statistics = 1.66 and the critical value for χ^2 statistics = 5.99.

Table 1 (con't.)

Results Based on the Ordinary Least Squares Regression
(t-statistics are in parentheses)

Firm No.	$\hat{\alpha}$	$\hat{\beta}$	Homoscedasticity* (White test)	Normality*
18	-.003	0.96[a]	3.907	40.97[a]
	(-0.37)	(5.92)		
19	.006	1.08[a]	0.816	21.74[a]
	(0.67)	(5.18)		
20	.010	0.76[a]	0.701	7.73[b]
	(1.20)	(4.25)		
21	.001	0.97[a]	4.080	32.42[a]
	(0.18)	(6.54)		
22	.003	0.88[a]	2.390	44.86[a]
	(0.47)	(5.74)		
23	.009	1.95[a]	13.834[a]	33.27[a]
	(1.08)	(10.41)		
24	.009	0.83[a]	11.539[a]	37.97[a]
	(1.31)	(5.13)		
25	-.001	1.31[a]	2.688	33.19[a]
	(-0.08)	(6.21)		
26	.008	0.83[a]	9.907[a]	13.64[a]
	(1.25)	(5.90)		
27	.006	0.89[a]	5.126	25.66[a]
	(1.00)	(6.74)		
28	.002	0.58[a]	0.048	19.31[a]
	(0.40)	(4.55)		
29	.011	0.94[a]	4.090	36.11[a]
	(0.68)	(2.68)		
30	-.003	1.05[a]	4.906	34.26[a]
	(-0.41)	(6.44)		
31	.024[b]	1.31[a]	3.629	17.40[a]
	(2.30)	(5.64)		
32	.011[b]	1.07[a]	4.704	29.44[a]
	(1.77)	(7.80)		
33	.009	1.15[a]	3.725	38.32[a]
	(0.97)	(5.31)		
34	.023[a]	1.27[a]	10.003[a]	18.21[a]
	(2.79)	(6.81)		
35	.007	1.71[a]	2.803	30.63[a]
	(0.76)	(8.72)		

*χ^2 test statistics.

[a]Significant at the 1% level; the critical value for t-statistics = 2.37 and the critical value for χ^2 statistics = 9.21.

[b]Significant at the 5% level; the critical value for t-statistics = 1.66 and the critical value for χ^2 statistics = 5.99.

Table 2

Results Based on the ARCH Model
(t-statistics are in parentheses)

Firm No.	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\gamma}_0$	$\hat{\gamma}_1$	Normality Test Statistics*
1	-.003	1.33[a]	.003[a]	.305[a]	33.37[a]
	(-.61)	(12.30)	(5.90)	(2.18)	
2	.004	0.95[a]	.007[a]	.172	22.56[a]
	(0.69)	(6.46)	(7.09)	(1.47)	
3	-.003	-0.98[a]	.002[a]	.142	19.14[a]
	(-0.095)	(12.51)	(7.62)	(1.59)	
4	.008[a]	0.64[a]	.008[a]	.275[a]	20.18[a]
	(3.61)	(12.15)	(6.68)	(2.40)	
5	.002	1.77[a]	.010[a]	.204	14.49[a]
	(0.23)	(10.48)	(6.85)	(1.61)	
6	.018[b]	-0.05	.011[a]	.166[b]	14.23[a]
	(2.24)	(-0.25)	(7.83)	(1.72)	
7	.008	-.216	.006[a]	.106	22.70[a]
	(1.39)	(-1.59)	(8.14)	(1.50)	
8	.011[b]	.784[a]	.003[a]	.310[b]	33.33[a]
	(2.23)	(7.03)	(6.11)	(2.29)	
9	.023[a]	1.74[a]	.017[a]	.077	20.75[a]
	(2.42)	(8.14)	(8.80)	(1.30)	
10	.005	1.02[a]	.003[a]	.241[b]	23.82[a]
	(1.10)	(10.44)	(6.63)	(1.90)	
11	-.003	1.18[a]	.003[a]	.205[b]	15.42[a]
	(-0.82)	(12.69)	(7.63)	(2.11)	
12	.016[a]	1.90[a]	.007[a]	.118	9.09[b]
	(2.51)	(13.64)	(7.98)	(1.44)	
13	.009[b]	0.98[a]	.004[a]	.182[b]	42.87[a]
	(1.76)	(8.67)	(7.12)	(1.84)	
14	.001	1.03[a]	.003[a]	.138[b]	16.11[a]
	(0.30)	(10.11)	(8.22)	(1.83)	
15	.011[b]	1.55[a]	.005[a]	.452[a]	19.38[a]
	(1.79)	(11.34)	(6.01)	(2.99)	
16	.017[a]	0.72[a]	.008[a]	.254[b]	33.37[a]
	(2.38)	(4.48)	(6.77)	(2.15)	
17	-.007	1.23[a]	.003[a]	.149	47.70[a]
	(-1.62)	(12.44)	(6.92)	(1.42)	

*χ^2 test statistics.

[a]Significant at the 1% level; the critical values for t-statistics = 2.37 and the critical value for χ^2 statistics = 9.21.

[b]Significant at the 5% level; the critical values for t-statistics = 1.66 and the critical value for χ^2 statistics = 5.99.

Table 2 (cont'd.)

Results Based on the ARCH Model
(t-statistics are in parentheses)

Firm No.	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\gamma}_0$	$\hat{\gamma}_1$	Normality Test Statistics*
18	-.003	0.92^a	$.004^a$	$.142^b$	40.61^a
	(-0.70)	(8.45)	(7.74)	(1.69)	
19	.004	1.09^a	$.006^a$	$.273^b$	21.86^a
	(0.75)	(8.11)	(6.91)	(2.18)	
20	.007	0.75^a	$.003^a$	$.392^a$	7.79^b
	(1.45)	(6.85)	(6.04)	(2.65)	
21	.0008	0.95^a	$.003^a$	$.137^b$	32.61^a
	(0.17)	(9.65)	(7.88)	(1.72)	
22	.003	0.89^a	$.003^a$	$.243^b$	44.96^a
	(0.70)	(8.98)	(5.68)	(1.69)	
23	.006	1.80^a	$.005^a$	$.221^b$	33.43^a
	(1.17)	(14.57)	(7.17)	(2.20)	
24	$.011^b$	0.84^a	$.003^a$	$.224^b$	37.94^a
	(2.29)	(7.86)	(6.55)	(1.96)	
25	-.00003	1.29^a	$.006^a$	$.183^b$	32.39^a
	(-0.005)	(9.39)	(7.25)	(1.81)	
26	.004	0.89^a	$.002^a$	$.506^a$	14.08^a
	(1.14)	(10.18)	(6.10)	(3.04)	
27	.006	0.82^a	$.002^a$	$.357^b$	25.69^a
	(1.62)	(9.79)	(6.04)	(2.19)	
28	-.0009	0.68^a	$.002^a$	$.244^b$	16.43^a
	(-0.03)	(8.15)	(7.42)	(2.33)	
29	.006	0.90^a	$.018^a$	$.138^b$	36.48^a
	(0.60)	(3.87)	(7.88)	(1.71)	
30	-.002	1.09^a	$.004^a$	.117	34.45^a
	(-0.33)	(10.07)	(8.12)	(1.62)	
31	$.024^a$	1.20^a	$.008^a$	$.151^b$	16.78^a
	(3.47)	(7.72)	(7.98)	(1.85)	
32	$.010^a$	0.95^a	$.002^a$	$.343^a$	27.83^a
	(2.55)	(11.09)	(6.61)	(2.76)	
33	.008	1.16^a	$.006^a$	$.210^b$	38.16^a
	(1.20)	(8.03)	(6.55)	(1.66)	
34	$.022^a$	1.15^a	$.005^a$	$.243^b$	18.17^a
	(4.12)	(9.39)	(6.72)	(1.92)	
35	.004	1.65^a	$.005^a$	$.316^b$	29.86^a
	(0.77)	(12.64)	(6.13)	(2.34)	

*χ^2 test statistics.

[a]Significant at the 1% level; the critical values for t-statistics = 2.37 and the critical value for χ^2 statistics = 9.21.

[b]Significant at the 5% level; the critical values for t-statistics = 1.66 and the critical value for χ^2 statistics = 5.99.