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EXPECTED RETURNS AND VOLATILITY IN EUROPEAN STOCK MARKETS

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Abstract

The type of return generating process we test here on three European markets are GARCH and AR-GARCH in mean models with innovations that have either normal or student-t densities with time dependant variances. These models are appealing in that they estimate time varying volatility in disturbances of stock returns series and ex-ante relationship between stock returns and volatility. Our results indicate that there is no statistically significant coefficient estimates for the volatility in the mean equation and that variance might not be appropriate as a measure of risk. Other proxies for risk should then be searched for.

I. Introduction

A considerable number of studies in financial economics, both empirical and theoretical, relate expected returns on common stocks to the notion of risk. These studies mainly measure a stock's risk as the covariance between its return and one or more variables. For instance, the capital asset pricing model of Sharpe (1964) relates returns of stocks to their covariances with the market portfolio's returns; the arbitrage pricing model of Ross (1976) relates stock returns to their covariances with several factors; and the consumption asset pricing model of Breeden (1979) relates stock returns to their covariances with the aggregate consumption. These models have been thoroughly tested, but, in recent years, the increasing evidence of time variation in expected returns and risk put into question the implications and relevance of these models. Many researchers have in turn re-examined financial valuation models in the conditional form that allow expected returns to vary over time (see Gibbons and Ferson (1985), Keim and Stambaugh (1986), and Campbell (1987)), or both expected returns and variance to be time varying (see French, Schwert, and Stambaugh (1987), Baillie and De Gennaro (1990)).

One point emerging from these studies, though not strongly conclusive, is that the use of variance to model risk might not be appropriate. Baillie and De Gennaro, for instance, conclude that their results "show almost no evidence of a relationship between mean returns on a portfolio of stocks and the variance or standard deviation of those returns. This implies that simple mean-variance models are inappropriate, and suggests the importance of further research using alternative measures of risk." The notion of variance as a sole proxy for risk has already been questioned in the literature. Among others, Kraus and Litzenberger (1976) developed a three moment model in which the investors are averse to variance but prefer positive skewness, and Price, Price, and Nantell (1982) and Bawa and Lindenberg (1977) used lower partial moments in their models.

Insofar these studies, which have been exclusively applied to the American markets, have not produced conclusive results. Whether the notion of variance is a good measure of risk in European stock markets is the concern of this paper.

The type of return generative processes we test here are GARCH and AR-GARCH in mean models with innovations that have either normal or student-*t* densities with time dependant variances. These models are appealing in the sense that they estimate time varying volatility in disturbances of stock returns series and ex-ante relationship between stock returns and volatility.

The structure of the paper is the following. Sections two and three present the data and the statistical analysis. In the fourth section autoregressive conditional heteroskedastic processes are discussed. The next section is then devoted to empirical results and their interpretations.

II. Data

For this study, we have selected the indices of the three large and active stock markets in Europe; namely France, Germany, and the U.K. for the period 1/1/1973 to 30/9/1991. As stock returns are often influenced by institutional features that vary considerably among countries in our sample and the

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composition of national stock market indices is rather different from each other, we used DATASTREAM[1] constructed indices for each country. These are all value weighted and are composed in the same way for each country. These indices are collected on a weekly basis and their returns are calculated as the difference in natural logarithm of two consecutive values, R_t - log(P_t) - log(P_{t-1}). The number of observations for each country is 978 for the period under consideration.

III. Statistical analysis

This section contains an analysis of the distributional and time-series properties of the stock market indices returns in the sample. A range of descriptive statistics are presented in Table 1. They are: mean, variance, skewness, and kurtosis. It can be observed that there are differences across the countries regarding the mean and the variance of the return series. Under the assumption of normality m_3 and m_4, the standard measures of skewness and kurtosis, have asymptotic distributions /V(0,6/*T*) and /V(3,24/*T*), respectively, where *T* is the sample size. All distributions are negatively skewed, indicating that they are nonsymmetric. Furthermore, they all exhibit statistically significant levels of kurtosis, which indicates that these distributions have fatter tails than normal distributions. Moreover the Bera and Jarque test (1982), i.e. $T(m_3^2/6 + (m_4 - 3)^2/24)$, that jointly tests if the third and fourth moments have values consistent with the null hypothesis of normality, is also statistically significant. Its values are all superior to the critical values for the χ^2 distribution with two degrees of freedom. The results confirm the well known fact that daily stock returns are not normally distributed, but are leptokurtic and skewed.

Furthermore, the Box-Pierce test statistic adjusted for heteroskedasticity, *Q{k),* as suggested by Diebold (1987), up to lag 20 is calculated and presented in Table 1. This is a joint test of the null hypothesis that the first *k* autocorrelation coefficients are zero. Under the null hypothesis, the adjusted Box-Pierce statistic,, follows a chi-square distribution with *k* degrees of freedom, where p(*i*) is the *i*-th autocorrelation. *S(i)* is a heteroskedasticity-consistent estimate of the standard error for the *i*-th sample autocorrelation coefficient,where $\gamma_R^2(i)$ is the i-th sample autocovariance of the square data and σ is the sample standard deviation of the data.

Table 1. Sample Statistics of Returns Series

Statistics	*France*	*Germany*	*U.K.*
Sample size	978	978	978
Mean (x 10^2)	0.1846	0.1047	0.1876
t(mean=0)	2.069	1.454	1.995
Variance (x10^2)	0.0778	0.0506	0.0865
m_3	-1.0386	-0.7049	-0.0856
m_4	6.7788	4.7995	11.3139
Bera and Jarque test	757.71	212.92	2817.83
First order autocorrelation	0.0507	-0.0257	-0.0856
	(0.0413)	(0.0538)	(0.0540)
Q(20)	24.0461	16.8962	20.1510
Q^2(20)	36.2990	67.5560	54.6910

Note: t-statistics significant at the one percent level are underlined. Numbers in parentheses are heteroskedasticity-consistent standard errors.

The values of *Q(20)* are not significant at the 5% level. Table 1 also presents $Q^2(20)$ which is the Box-Pierce statistic based on the squared return series. Under the null hypothesis of conditional homoskedasticity, the statistic $Q^2(k)$ has an asymptotic chi-square distribution with *k* degrees of freedom. The null hypothesis is strongly rejected for all countries.

Looking at the first order autocorrelation coefficients, which are also reported in Table 1, we can

observe that only that of the UK is significant. This implies the rejection of a white noise process, i.e. uncorrected process, for this country.
One way to generate an uncorrelated series for the UK is to apply an *AR(1)* model, that is:

$$R_t = \phi_0 + \phi_1 R_{t-1} + \varepsilon_t \quad (1)$$

The estimates of the above regression model for the UK are presented in Table 2. In order to observe the behavior of the residuals ε_t obtained from equation (1), we applied the same tests as for the return series. As far as the distribution of residuals is concerned, it appears that it is still leptokurtic and skewed in comparison with the normal distribution. The Bera-Jarque test also rejects the null hypothesis of normality of the series. The first order autocorrelation coefficient is not significantly different from zero, and the insignificant value of *Q(20)* indicates that the *AR(l)* transformation of the returns provides an uncorrected series of residuals.

Table 2. The Autoregressive Model for the UK

	Estimates of the model
$\phi_0 (\times 10^2)$	0.1714
$t(\phi_0)$	1.8225
ϕ_1	0.0856
$t(\phi_1)$	<u>2.6822</u>
	Statistics of weekly residuals series
Mean (x 10^2)	0.0000
t(mean=0)	0.0000
Variance (x 10^2)	0.0860
m_3	<u>-0.1719</u>
m_4	<u>10.4725</u>
Bera and Jarque test	<u>2280.23</u>
First order autocorrelation	-0.0063 (0.0530)
Q(20)	16.8310
$Q^2(20)$	<u>68.6040</u>

Note: t-statistics significant at the one percent level are underlined. Numbers in parentheses are heteroskedasticity-consistent standard errors.

Furthermore, the values of $Q^2(20)$ decisively reject the null hypothesis of conditional homoskedasticity.
The excess kurtosis observed in returns or residuals series of the three countries in our sample can be related to conditional heteroskedasticity, that is, excess kurtosis can be due to a time varying pattern of the volatility.

IV. Conditional volatility and returns

One of the recent proposed class of return generating processes in the literature that can describe the behavior of stock return series is the class of autoregressive conditional heteroskedastic processes introduced by Engle (1982) and its generalized version by Bol-lerslev (1986,1987). In these processes the conditional error follows a particular distribution with conditional variance defined as a linear function of past square errors and lagged conditional variance. These models allow for volatility clustering, that is, large changes are followed by large changes, and small by small, which has long been recognized as an important feature of stock returns behavior. Empirical studies have shown indeed that such processes are successful in modelling various time series. See, for example, in the context of foreign exchange markets, Hsieh (1989), and in the context of stock markets, Chou (1988) and Akgiray (1989).

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The Generalized Autoregressive Conditional Heteroskedastic model, denoted by *GARCH(p,q)*, is the following:

$$\varepsilon_t \mid \psi_{t-1} \sim D(0,h_t)$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \qquad (2a)$$

with $p > 0$; $\alpha_i; > 0,..., p$, $q \geq 0$ and $\beta_i > 0$, $j = 1 ,...,q$ and where ψ_t is the information set of all information through time t, and the ε_t are obtained from a linear regression model, that is, for the UK and $\varepsilon_t = R_t - \phi_0$ for the other two countries. The conditional

error, ε_t, follows a certain distribution with mean 0 and variance h_t.

Concerning the UK market, an alternative model, presented by Bera, Higgins, and Lee (1992), is the following[2]:

$$\varepsilon_t = R_t - \phi_0 - \phi_1 R_{t-1}$$

$$\varepsilon_t \mid \psi_{t-1} \sim D(0,h_t)$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i R_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \qquad (2b)$$

While in a conventional GARCH model, e.g. in 2a, autocorrelation and ARCH properties are tackled separately, this model considers these two properties simultaneously. This model is denoted as AR-GARCH.

Engle, Lilien, and Robins (1987) proposed the GARCH in mean or GARCH-M model that allows the returns to be a function of conditional volatility. In this case the linear regression model of the returns becomes:

$$\varepsilon_t + R_t - \phi_0 - \phi_1 R_{t-1} - \delta f(h_t) \qquad (3)$$

where δ represent the impact of volatility on returns and f is a function of the volatility, that is generally, the variance, the standard deviation or the logarithm of variance. The coefficient ϕ_1 is zero for France and Germany and different from zero for the UK. For the latter country, the AR-GARCH in mean will be also estimated. Under the mean-variance hypothesis, the coefficient of the conditional volatility in the mean equation, δ, should be positive, indicating large values of conditional volatility to be associated with large returns.

Original GARCH models assume that the conditional errors were normally distributed. This allows unconditional error distributions to be leptokurtic. However, later studies have shown that conditional normal distribution might not fully explain the high level of kurtosis in observed distributions of daily return series. It has been suggested in the literature that the assumption of a leptokurtic conditional distribution in GARCH models might be more appropriate since such distribution can better account for the level of kurtosis observed in financial data than does the normal conditional distribution. This allows a distinction between conditional heteroskedasticity and a conditionally leptokurtic distribution, either of which could generate the fat-tailedness observed in the data. Various conditional leptokurtic distributions have been suggested in the literature (Baillie and Bollerslev 1989, Hsieh 1989), and it is generally accepted that the t-distribution, originally proposed by Bollerslev (1987), performs rather better than other distributions.[3]

The sum of $\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j$ in the conditional variance equations measures the persistence of the volatility. If this sum is equal to one, the GARCH process becomes an integrated GARCH or IGARCH process (Engle and Bollerslev 1986). In such model the current information remains important for the forecast of the conditional variance over all future horizons and it also implies an infinite variance of the unconditional distribution of ε_t.

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A. Estimation and Testing

All GARCH in mean models are estimated using a FORTRAN program which employs the nonlinear optimization technique of Berndt, Hall, Hall, and Hausman (1974) to compute maximum likelihood estimates.[4] Given the return series and initial values of ε_l and h_l, for l = 0,...,r and with $r = max(p,q)$, the log-likelihood function we have to maximize for a *GARCH(p,q)* model with normal distributed conditional errors is the following:

$$L(\phi \mid p,q) = -\frac{1}{2}T\ln(2\pi) + \sum_{t=r}^{T} \ln\left(\frac{1}{\sqrt{h_t}}\right)\exp\left(\frac{-\varepsilon_t^2}{2h_t}\right) \tag{4}$$

where
T = the number of observations; h_t = the conditional variance;
ε_t^2 = the residuals obtained from the appropriate model for the country under consideration.
In the case of *t*-distributed conditional errors, the log-likelihood function for this model is:

$$L(\phi \mid p,q) = \sum_{t=1}^{T}\left[\log\left(\Gamma(\frac{\upsilon+1}{2})\right) - \log\left(\Gamma(\frac{\upsilon}{2})\right) - \frac{1}{2}\log(\upsilon-2)h_t - \frac{1}{2}(\upsilon+1)\log(1+\varepsilon_t^2 h_t^{-1})\,(—2)^{-1}\right] \tag{5}$$

where $\Gamma(.)$ denotes the gamma function and υ is the degree of freedom. If $1/\upsilon \to 0$ the *t*-distribution approaches a normal distribution, but for $1/\upsilon > 0$ the *t*-distribution has fatter tails.
In this paper, we only apply a GARCH(1,1) process as it has often been proved that this model fits better stock returns than do GARCH(p,g) models with $p + q \geq 3$.
In order to test for the relative fit of the various models, the likelihood ratio test (LR) will be employed, where $L(\phi_n)$ and $L(\phi_a)$ denote the maximized likelihood functions estimated under the null hypothesis and the alternate hypothesis. Under the null hypothesis LR is chi-square distributed with degrees of freedom, *k*, equal to the difference in the number of parameters under the two hypotheses. The null hypothesis is rejected if the value of the test statistic LR is too large, that is, if LR $\geq X_k^2$ distribution.

B. Empirical Results

Table 3 and Table 4 give the results of applying GARCH-M models for the three countries assuming a conditional normal and student-*t* distribution respectively. The results for the UK when we apply the model of Bera, Higgins, and Lee are reported in Table 5 for both type of distributions. We used the variance, the standard deviation and the logarithm of the variance as proxies for volatility in the conditional mean equation (3). As results were very similar, we only report those for the standard deviation.
Looking at Tables 3 and 4 we observe that the maximized values of the loglikelihood for the model with conditional *t*-distributed errors are larger than those of normally distributed ones in two cases out of three. The values of LR are respectively 75.62, -6.04 and 21.82 indicating that the *t*-distributed error model is better than the normal one for France and the UK. As for Germany, there is no statistically significant difference between the two models. All models have statistically significant. GARCH parameter estimates of α and β coefficients. Their sum is also less than the unity, indicating that the models are second order stationary and that their second moments exist. This result is expected. While integrated processes are often observed when daily data are used, using weekly data reduces the possibility of observing such process (Baillie and Bollerslev, 1989).

Table 3. GARCH in Mean Estimates (with normally distributed conditional errors)

	France	*Germany*	*U.K.*
$\phi_0(\times 10^2)$	0.1684	0.5649	0.2758
$t(\phi_0)$	0.3101	1.1752	0.9478
ϕ_1	—	—	0.1043
$t(\phi_1)$	—	—	2.7464
$\alpha_0(x\ 10^2)$	0.0162	0.0078	0.0044

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$t(\alpha_0)$	6.2307	3.1730	4.4598
α_1	0.2018	0.1094	0.1848
$t(\alpha,)$	8.0905	4.8238	10.2288
β_1	0.6053	0.8199	0.7644
$t(\beta_1)$	16.5942	22.8099	33.2591
δ	0.0138	-0.1120	-0.0292
$t(\delta)$	0.0647	-0.7218	-0.2316
$\sum^P_{i=1} \alpha_1+\sum^q_{j=1} \beta_1$	0.8071	0.9293	0.9492
Log-Likelihood	2148.22	2434.70	2214.37
m_3	-0.9550	-0.3360	-0.6373
m_4	5.6505	6.7211	3.9374
Bera and Jarque test	434.92	582.63	54.19
Q(20)	28.366	16.095	17.571
$Q^2(20)$	8.9402	47.6505	10.2669

Note: t-statistics significant at the 1 % level are underlined.

The interesting feature of Tables 3 and 4 is that they show that none of the coefficient estimates $\hat{\delta}$, representing the relationship between the return and conditional standard deviation, is statistically significant. Furthermore the sign of the coefficient is negative for the Germany and the UK under normally distributed conditional errors and for the UK under *t*-distributed conditional errors. Such results implies a negative risk premium for holding stocks, i.e. the market in this case. Our results are in contradiction with those of French et al. (1987) who found a positive risk premium for the US market when applying a GARCH-M model with normally distributed conditional errors, but are consistent with those of Bailey and De Gennaro (1990).
A comparison of the values of m_3, and m_4, in Tables 3 and 4, that is, the skewness and kurtosis of the standardized residuals respectively, with those reported in Table 1 for the return series shows that the GARCH-M models have substantially reduced the excess fat-tailedness in the data in the case of the UK. The values of the Bera-Jarque test are nevertheless still significant. The fact that all estimates of the inverse of the degree of freedom parameter, 1/υ, in Table 4, are highly significant gives support for the *t*-distribution of conditional errors.

Table 4. GARCH in Mean Estimates (with t-distributed conditional errors)

	France	*Germany*	*U.K.*
$\phi_0(\times 10^2)$	-0.2244	-0.0739	0.2948
$t(\phi_0)$	-0.4562	-0.3579	1.007
ϕ_1	—	—	0.0775
$t(\phi_1)$	—	—	2.1546
$\alpha_0(x\ 10^2)$	0.0065	0.0007	0.0041
$t(\alpha_0)$	3.4104	2.3752	4.1878
α_1	0.0810	0.0901	0.1481
$t(\alpha_1)$	3.7289	6.0526	7.8997
β_1	0.8095	0.8929	0.7826
$t(\beta_1)$	18.8439	56.3100	31.6989
δ	0.2137	0.1191	-0.0197
$t(\delta)$	1.0490	1.0335	-0.1507

$1/\upsilon$	0.0625	0.0351	0.0449
$t(1/\upsilon)$	**	<u>19.3026</u>	**
$\Sigma_{i=1}^{p} \alpha_i + \Sigma_{j=1}^{q} \beta_j$	0.8905	0.9830	0.9307
Log-Likelihood	2186.03	2431.68	2225.28
m_3	<u>-1.1040</u>	<u>-0.3522</u>	<u>-0.6449</u>
m_4	<u>7.2261</u>	<u>5.7219</u>	<u>4.0326</u>
Bera and Jarque test	<u>926.33</u>	<u>322.12</u>	<u>111.23</u>
$3(\hat{\upsilon}-2)/(\hat{\upsilon}-4)$	3.5000	3.2449	3.3284
Q(20)	29.6645	15.4558	15.9949
$Q^2(20)$	8.5176	37.2796	12.9626

*Notes: t-statistics significant at the 1 % level are underlined. **indicates very large significant t-values.*

[illegible] conditional errors are normally distributed but not when they are *t*-distributed. This confirms that the latter model fits the return series in our sample reasonably well. However, the estimated GARCH in mean parameter are all insignificant whatever the distribution for all three countries.

The results of the AR-GARCH in mean model which allows for simultaneous estimation of autocorrelation and GARCH coefficients for both types of conditional distribution are reported in Table 5. The student-*t* distribution again fits the data better than the normal distribution.

Table 5. AR-GARCH in Mean Estimates for the UK

	Normal distribution	*t-distribution*
$\phi_0 (\times 10^2)$	0.3264	0.3157
$t(\phi_0)$	1.1559	1.0276
ϕ_1	0.1266	0.0847
$t(\phi_1)$	<u>3.1036</u>	<u>2.3266</u>
$\alpha_0 (x\ 10^2)$	0.0041	0.0041
$t(\alpha_0)$	<u>4.1737</u>	<u>3.1944</u>
α_1	0.1858	0.1392
$t(\alpha_1)$	<u>10.0443</u>	<u>5.5619</u>
β_1	0.7661	0.8000
$t(\beta_1)$	<u>32.7560</u>	<u>25.0075</u>
δ	-0.0717	-0.0443
$t(\delta)$	-0.5867	-0.3314
$1/\upsilon$	—	0.1012
$t(1/\upsilon)$	—	<u>44.0977</u>
$\Sigma_{i=1}^{p} \alpha_i + \Sigma_{j=1}^{q} \beta_j$	0.9518	0.9392
Log-Likelihood	2213.76	2229.76
m_3	<u>-0.3234</u>	<u>-0.3429</u>
m_4	<u>1.5046</u>	<u>1.8137</u>

Bera and Jarque test	108.17	76.52
$3(\hat{\upsilon}-2)/(\hat{\upsilon}-4)$	—	4.0207
Q(20)	17.1585	18.6127
$Q^2(20)$	17.0371	17.0029

Note: t-statistics significant at the 1 % level are underlined.

The values of the loglikelihood function are 2213.76 and 2229.76 under the normal and student-*t* distributions respectively. When we compare these values with those obtained using the GARCH in mean models, there is a slight improvement only in the case of the student-*t* distribution. Most of the results are very similar to those of the GARCH in mean model. The values of the autocorrelation coefficients and GARCH coefficients are close to those previously obtained in Table 3 and Table 4 and they are also statistically significant. Again the coefficient estimate $\hat{\delta}$, is negative and not statistically significant, which confirms the above results. As for the distribution of the residuals, the normality is still rejected on the basis of the values of the direct tests of the skewness and the kurtosis and the joint test of Bera-Jarque. Both Box-Pierce on the standardized and squared residuals do not indicate the presence of serial correlation or second order dependance as well. The process is still second order stationary as the sum of the GARCH parameters is less than one.

V. Conclusion

In this paper we studied the relationship between stock returns and volatility for three European stock markets using the GARCH and AR-GARCH in mean models with conditional errors that are either normally or *t*-distributed. Although our results clearly indicate that the class of autoregressive conditional heteroskedastic models is generally consistent with the stochastic behavior of European equity indices, we do not find statistically significant coefficient estimates for the volatility in the mean equation. Thus our results suggest that asset pricing models relating return to variance might not be appropriate and that one should look for risk proxies other than the variance.

Notes

1. DATASTREAM is a UK incorporated data service company.
2. We thank the anonymous referee for suggesting this alternative model.
3. It is possible to avoid distributional assumptions in the estimation of GARCH models by using the Generalized Method of Moments. Rich, Raymond, and Butler (1991) showed indeed that it is a useful alternative to maximum likelihood estimation of GARCH models.
4. This program has been developed by Ken Kroner at the University of California. It was kindly provided to us by Robert Engle.

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