

A REVIEW OF STOCK PRICE VOLATILITY STUDIES ON CASH AND FUTURES MARKETS

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ABSTRACT

The aim of this paper is to review studies on stock price volatility taking into account some of the factors that may affect their financial behaviour within the cash and futures stock markets. In order to fulfill our aim we refer to a number of studies across Europe and the USA taking into consideration studies that occurred in finance before the year 1998. This is the crucial year which we have as a limit for the purpose of our current review. We mainly present the research question, the methodology, data and results of each study based mainly on univariate ARCH type family models. This paper could be found useful for those researchers and academicians who want to measure the validity of ARCH type models in order to investigate the distribution of stock price returns.

INTRODUCTION

Since the ability of volatility clustering prediction has been a controversial issue for many years, a large number of studies have investigated the relationship between volatility and expected returns producing inconsistent results. The issue of volatility clustering, however now is predictable, due in part to the use of GARCH methodology. The issue is now transferred to volatility forecasting

ability, which still remains unresolved, due in part to the drawbacks of each model.

In this paper, the literature of stock price volatility is reviewed on seven subtitles. Section 2 examines the evidence on cash and futures markets. This section is divided into seven subsections. In the first section, we review the literature on heteroskedastic behaviour of expected returns, when the risk changes, referring to the development of ARCH type models, in relation to the past information and asymmetric error terms, that explains the character of conditional heteroskedastic models. In the second part of section 2, evidence on volatility persistence are available, showing that the volatility persistence is a difficult procedure, and as a result only the magnitude of time-varying risk can be defined, not its persistence along time. In the third part of section 2, evidence on stock price volatility autocorrelation summarises the process that is followed by stock market returns, namely high-moment processes. In the fourth part of section 2, review on forecasting and filtering performance of ARCH models determine that the international CAPM model does not hold, and in addition the predictable process of future volatility returns is still misspecified. In the fifth part of section 2, evidence on leverage and interest rate effects show that the level of interest rate is not actually the big enemy for investors and also the size effects do not play important role at the aggregate level of stock price volatility. In the sixth part of section 2, evidence on trading volume and GARCH effects are provided. The main findings is that GARCH effects are superior to trading volume and the explanation power of trading volume is reduced, when GARCH methodology is used. In the seventh part of section 2, evidence on future markets proposes that stock markets do not be led by the dynamics of future markets. So, the dynamics of each market, cash or future market should be examined separately, at least in terms of volatility. Finally, the section 3 summarises the whole paper throughout the most important findings.

EVIDENCE ON STOCK AND FUTURE MARKETS

Conditional Heteroskedasticity-Information Arrival-Asymmetric Effects

Engle (1982) supported that traditional econometric models assume a constant one-period forecast variance. To generalise this implausible assumption, a new class of stochastic processes called autoregressive conditional heteroskedastic (ARCH) processes were introduced. These were mean zero, serially uncorrelated processes with non-constant variances conditional on the past, but constant unconditional variances. For such processes, the recent past gives information about the one-period forecast variance.

Engle and Bollerslev (1986) drowned attention to the distinction between the GARCH(1,1) and IGARCH(1,1) models, arguing that these can be considered analogous to the ARIMA(1,0,0) and ARIMA(0,1,0) models. Because of the

discontinuity at the unit root boundary, there was speculation that a similar distribution discontinuity would occur in the conditional variance case. The analogy of the IGARCH(1,1) to a random walk with drift was at best superficial, and has been discussed by Engle and Bollerslev (1986), and Nelson (1990). Nelson (1990) implied that while the process in the GARCH (1,1) model was covariance stationary, strictly stationary, and ergodic, in the IGARCH(1,1) model it was not covariance stationary, but it was strictly stationary and ergodic, distinguishing it from the random walk with drift case.

Bollerslev (1986) proposed the natural generalisation of the ARCH(Autoregressive Conditional Heteroskedastic) process which had been introduced by Engle (1982) to allow for past conditional variances in the current conditional variance equation. While conventional time series and econometric models operated under an assumption of constant variance, the ARCH process allowed the conditional variance to change over time as a function of past errors leaving the unconditional variance constant.

Lumsdaine (1996) extended the arguments of Hong (1987) to prove that the quasi-maximum likelihood estimators of all the parameters in the GARCH(1,1) and IGARCH(1,1) models were consistent and jointly asymptotically normal. Even without the assumption of a finite fourth moment, these results obtained using alternative moment conditions that were satisfied in both models. In contrast to the case of a unit root in the conditional mean, the presence of a 'unit root' in the conditional variance did not affect the limiting distribution of the estimators in both models, estimators remained normally distributed.

Engle et al. (1987) extended the simple ARCH technique of measuring conditional variances to the ARCH-M model where the conditional variance was determinant of the current risk premium, and thus entered the forecasting equation of expected financial returns. The model was applied to three different interest rate data sets. In most cases the ARCH process and the time varying risk premium were highly significant.

Akgiray (1989) presented evidence about the time-series behaviour of stock prices. Daily return series exhibited significant levels of second-order dependence, and they could not be modelled as linear white-noise processes. A reasonable return-generating process was empirically shown to be a first-order autoregressive process with conditionally heteroskedastic innovations. In particular, generalised autoregressive conditional heteroskedastic GARCH(1,1) processes fitted to data very satisfactory. Various out of sample forecasts of monthly return variances were generated and compared statistically. Forecasts based on the GARCH model were found to be superior.

Schwert and Seguin (1990) used predictions of aggregate stock return variances from daily data to estimate time-varying monthly variances for size-ranked portfolios. They proposed and estimated a single factor model of heteroskedasticity for portfolio returns. This model implied time-varying betas. Accounting for heteroskedasticity, increased the evidence that risk-adjusted

returns were related to firm size. Their portfolio volatilities predicted by this model, were similar to those predicted by more complex multivariate generalised-autoregressive-conditional-heteroskedasticity (GARCH) procedures.

Baillie and Degennaro (1990) used GARCH in mean models to examine the relationship between mean returns on stock portfolio and its conditional variance or standard deviation. Examined the relationship between stock returns and volatility using student-t density, they found that it provides a good description of daily and monthly returns data. Controlling for excess kurtosis by using the student-t density it was found to be important, and the estimated models showed very little evidence for a statistically significant relationship between a stock portfolio's return and its own volatility. Their results suggested that traditional two-parameter models relating portfolio means to variances were inappropriate and indicated the need for research into other measures of risk.

Nelson (1991) criticised the GARCH models in modelling the relationship between conditional variance and asset risk premium. These models had at least three major drawbacks in asset pricing applications: (i) researchers beginning with Black (1976) found a negative correlation between current returns and future returns volatility. GARCH models ruled this out by assumption, (ii) GARCH models imposed parameter restrictions that were often violated by estimated coefficients and that may unduly restrict the dynamics of the conditional variance, (iii) interpreting whether shocks to conditional variance 'persist' or not was difficult in GARCH models, because the usual norms measuring persistence often did not agree. He proposed a new form of ARCH that met these objections.

Haugen, Taylor, and Torous (1991) estimated volatility changes in daily returns to the Dow Jones industrial Average over the sample period 1897 through 1988. This allowed a direct investigation of the reaction of the level of stock prices and subsequent expected returns to these estimated changes in volatility. They provided empirical evidence consistent with relatively large and systematic revisions of stock prices and subsequent expected returns to volatility changes. However, there appeared to be an asymmetry in the market's reaction to volatility increases as opposed to volatility decreases. They concluded that the majority of volatility changes could not be associated with the release of significant economic information.

Chan, Karolyi, and Stulz (1992) found that there was a significant foreign influence on the risk premium for US assets. Using a bivariate GARCH-M process, they found that the conditional expected excess return on US stocks was positively related to the conditional covariance of the return of these stocks with the return on a foreign index but was not related to its own conditional variance. Furthermore, they were unable to reject the international version of the CAPM.

Poon and Taylor (1992) attempted to quantify the relationship between stock returns and volatility because the previous attempts had produced conflicting conclusions in US studies. They examined this issue in UK context using daily, weekly, fortnightly and monthly returns on the financial times All- share index from January 1965 to December 1989. Volatility estimates were obtained from monthly sample variances and ARCH models. Expected returns were shown to have had a positive, though not statistically significant relationship between the unexpected components of the returns and volatility series: They found evidence for a negative relationship but only when volatility expectations were represented by standard deviations.

Campbell and Hentschel (1992) said that it 'seems' that an increase in stock market volatility, raised required stock returns, and thus lowered stock prices. They developed a formal model of this volatility feedback effect using a simple model of changing variance (a quadratic generalised autoregressive conditionally heteroskedastic, or Q-GARCH model). Their model was asymmetric and helped to explain the negative skewness and excess kurtosis of the US monthly and daily stock returns over the period 1926-1988. They found that volatility feedback normality had little effect on returns, but it could be important during periods of high volatility.

Engle and Ng (1993) defined the news impact curve which measured how new information was incorporated into volatility estimates. Various news and existing ARCH models including a partially nonparametric were compared and estimated with daily Japanese stock return data. New diagnostic tests were presented which emphasised the asymmetric volatility response to news. Their results suggested that the model by Glosten, Jagannathan, and Runkle was the best parametric model. The EGARCH model also could capture most of the asymmetry; there was evidence that the variability of the conditional variance implied by the EGARCH methodology was too high. Glosten, Jagannathan, and Runkle (1993) found support for a negative relationship between conditional expected monthly returns and conditional variance of monthly return, using a GARCH-M model modified by allowing (1) seasonal patterns in volatility, (2) positive and negative innovations to returns having different impacts on conditional volatility, and (3) nominal interest rates to predict conditional variance. Using the modified GARCH-M model, they also showed that monthly conditional volatility might not be as persistent as was thought. Positive unanticipated returns appeared to result in a downward revision of the conditional volatility whereas negative unanticipated returns resulted in an upward revision of conditional volatility.

Among the intertemporal depended models for conditional heteroskedasticity, those with a leverage (or asymmetry) effect were superior. The Glosten, Jagannathan, and Runkle specification was the most descriptive for individual stocks, while Nelson's exponential model was the most likely for stock indexes. Kim and Kon (1994) compared econometric model specifications that had been

proposed to explain the commonly observed characteristics of the unconditional distribution of daily stock returns. The empirical results indicated that the most likely ranking was: a, intertemporal depended models, b. student t, c. generalised mixture of normal distribution, d. poisson jump and e. the stationary normal.

Hertog (1994) used a composite GARCH model to decompose the conditional variance for US excess stock returns into a (near)-permanent and a transitory component. Both components were required for an adequate modelling of heteroskedasticity. However, for pricing the transitory component did not seem to be important; the results of a time-varying parameter model indicated there were no periods in which this component was significantly related to excess reruns. This could not be explained by an insignificant risk-return trade-off. For the permanent volatility component, significant mean-variance coefficients were found for a period of almost 20 years.

Corhay and Rad (1994) indicated that conditional heteroskedasticity was a prime feature of daily returns behaviour of five European equity indices. They exhibited non linear dependence that could not be captured by the random walk model. The class of autoregressive conditional heteroskedastic models was generally consistent with the stochastic behaviour of these return series. The evidence presented by them revealed that the GARCH-t(1,1), i.e. a GARCH model with conditional errors that were t-distributed, fitted the data best. Thus, their results confirmed that this class of models was also appropriate for studying the behaviour of stock returns on a small equity market. They also supported that GARCH models could indeed provide better forecasts of volatility than the usual historical estimates and led to improved valuation models.

Nicholls and Tonuri (1995) presented an overview of the GARCH family of variance models and examined the behaviour of Australian aggregate stock market volatility over the period 1988-1991 using the GARCH framework. Stock return data was typically negatively skewed and this empirical observation encouraged the development of GARCH-type models that attempted to incorporate such asymmetry in their structure. When applied to recent Australian daily stock return data, the asymmetric EGARCH(1,1) model was found to provide a suitable description of the variance of the data. The augmented version of the EGARCH model is

$$y_t = \beta R_t + u_t \quad (5)$$

where, $h_t^2 = V(u_t / \Omega_{t-1}) = E(u_t^2 / \Omega_{t-1})$. However, for h_t^2 , Nelson (1991) used an exponential functional form, which is written as:

$$\log h_t^2 = \alpha_0 + q \sum_{i=1}^q \alpha_i (u_{t-i} / h_{t-i}) + q \sum_{i=1}^q \alpha_i (|u_{t-i} / h_{t-i}| - \mu) + p \sum_{i=1}^p \phi_i \log h_{t-i}^2 \quad (6)$$

where, $\mu = E(|u_t / h_t|)$

The value of μ depends on the density function assumed for the standardised disturbances, $\varepsilon_t = u_t/h_t$. We have: $\mu = (2/\pi)^{1/2}$, if $\varepsilon_t \approx N(0,1)$ (7)

Existence of the unconditional variance required that $1 - \rho \sum_{i=1}^p \varphi_i \varepsilon_t^i = 0$. It is only required that the roots of the above equation fall outside the unit circle.

The unconditional variance of u_t in this case does not have a simple form. However, if $\rho \sum_{i=1}^p \varphi_i \varepsilon_t^i < 1$ then the log of unconditional variance will be given by: $\log(h_t^2) = \alpha_0 (1 - \rho \sum_{i=1}^p \varphi_i \varepsilon_t^i)^{-1}$. Thus, unlike the GARCH-M model, the EGARCH-M model always yields a positive conditional variance.

Hentschel (1995) developed a parametric family of models of generalised autoregressive heteroskedasticity (GARCH). The family nested the most popular symmetric and asymmetric GARCH models, thereby highlighting the relationship between the models and their treatment of asymmetry. Furthermore, the structure permitted nested tests of different types of asymmetry and functional forms. Daily US stock return data rejected all standard GARCH models in favour of a model in which, roughly speaking, the conditional standard deviation depended on the shifted absolute value of the shocks raised to the power three halves and also past standard deviations.

Theodossiou and Lee (1993) presented evidence on the stochastic behaviour of weekly stock market returns and the relationship between stock market volatility and expected returns for ten industrialised countries using the GARCH-M model. *The GARCH-M model can be written as follows:*

$$y_t = \beta R_t + \gamma h_t^2 + u_t \quad (1)$$

where,

$$h_t^2 = V(u_t / \Omega_{t-1}) = E(u_t^2 / \Omega_{t-1}) = \alpha_0 + \alpha \sum_{i=1}^q u_{t-i} + \rho \sum_{i=1}^p \varphi_i h_{t-i}^2 \quad (2)$$

and Ω_{t-1} is the information set at time $t-1$, containing observations on lagged values of R_t and h_t ; namely $\Omega_{t-1} = (h_{t-1}, h_{t-2}, \dots, R_{t-1}, R_{t-2}, \dots)$. The unconditional variance of u_t is constant and is given by: $V(u_t) = \sigma^2 = \alpha_0 / (1 - \alpha - \rho \sum_{i=1}^p \varphi_i) > 0$ (3) and the necessary condition for (1) to be covariance stationary is given by: $\alpha \sum_{i=1}^q \alpha_i + \rho \sum_{i=1}^p \varphi_i < 1$ (4). In addition to the restrictions (3) and (4) Bollerslev (1986) also assumed that $\alpha_i \geq 0, i=1, 2, \dots, q$, and $\varphi_i \geq 0, i=1, 2, \dots, p$. Although these additional restrictions were sufficient for the conditional variance to be positive, they were not necessary (Nelson and Cao, 1992). The countries were Australia, Belgium, Canada, France, Italy, Japan, Switzerland, the United Kingdom, the United States, and Germany. Three alternative specifications for the relationship between conditional variance and expected stock market returns were tested. These included square root, logarithmic, and linear specifications. They found strong conditional heteroskedasticity to be present in the return series of all markets, indicating the presence of volatility clustering. No relationship was found between expected returns and conditional volatility of returns in any of the ten markets. Also, significant serial correlation was present in the return

series for the markets of Australia, Belgium, Canada, France, and Italy, thus prices in these markets were incompatible with the Martingale model.

Giannopoulos (1995) applied an alternative approach for assessing securities' risk. Various authors argued that security returns were not homoskedastic but exhibited variations over time. They observed that large changes tended to be followed by more large changes in either direction, and so volatility should be predictably high after large changes. This phenomenon of securities' volatility, referred to as clustering, had important implications for security pricing and risk management. Among the most popular techniques currently used to capture the clustering effect and to forecast future volatility were those belonging to the family of Autoregressive Conditional Heteroskedastic (ARCH) models. The main aim of the author was to investigate whether such volatility modelling could be used to capture the time variation not only in the total risk of a security return but also its systematic and unsystematic components. Using weekly local stock market data, the time varying beta with the world index had been estimated via a bivariate GARCH-M model. The GARCH-M parameterization used by him was a dynamic specification that could not be rejected for 11 out of 13 local portfolios. The results provided evidence that both the systematic and non-systematic counterparts were also changing over time. However, in some markets those risk changes might take place with some delay. This suggested that some of the low correlation coefficients computed for certain stock market returns might not be due to differences in business cycles among those countries, but may be caused by the non-synchronous response to world market developments. This finding should have important implications in many investment decisions such as portfolio selection, market timing and risk hedging.

Foster and Nelson (1996) supported that it was widely known that the conditional covariance of asset returns changes over time. Researchers doing empirical work adopted many strategies for accommodating conditional heteroskedasticity. Among the popular strategies were: (a) chopping the available data into short blocks, (b) performing one-sided rolling regressions, in which only data from, say, the preceding five year period was used to estimate the conditional covariance of returns at a given date, and (c) performing two-sided rolling regressions, in which covariance were estimated for each date using, say, five years of lags and five years of leads. They developed continuous record asymptotic approximations for the measurement error in conditional variances covariance when using these methods. They devised asymptotically optimal window lengths for standard rolling regressions. They estimated volatility on the S and P 500 stock index using daily data from 1928 to 1990, and found that there was significant serial correlation of about 6% at one lag, mainly caused by thin trading of the stocks in the underlying index.

Chelley and Steeley (1996) used an augmented ARMA(1,1)-GARCH(1,1)-M specification to model volatility transmission between capitalisation-based

portfolios of UK stock returns. In addition, their model was able to capture the conditional heteroskedasticity in the return series and the important cross and own serial small firms. However, a shock to the volatility of returns for a small firm portfolio had a much larger impact than a shock to the volatility of returns for a large firm portfolio. Moreover, shocks to volatility tended to come not only from that particular portfolio, but also from portfolios of larger firms. In contrast, volatility shocks did not spill-over from small firm portfolios to large firm portfolios. To the extent that these results implied regularities in the process generating and transmitting volatility in the UK stock market, they would be useful information for financial risk managers.

The study of Islam and Landecc (1997) contained a detailed analysis of time series properties of the stock market index of Greece, using monthly data from December 1993 through December 1994 collected from the international finance corporation. The study applied the ARCH(1) and GARCH(1) models in order to investigate volatility in return series. GARCH(1,1) model could adequately describe the stock market behaviour of Greece which was much smaller and thinner than that of other developed stock markets in Europe. The coefficient of ARCH(1) indicated that the current period variances were higher if the past period had large disturbances. In addition, the coefficient of GARCH(1) indicated that the effect persisted for a long time. Thus, there was strong evidence of conditional heteroskedasticity.

Fornari and Mele (1997) developed two conditionally heteroskedastic models which allowed an asymmetric reaction of the conditional volatility to the arrival of news. Such a reaction was induced by both the sign of past shocks and the size of past unexpected volatility. The proposed models were shown to coverage in the distribution of absolutely continuous 'ito' diffusion processes, as happened for other heteroskedastic formulations. The volatility-switching ARCH differed from the existing asymmetric models insofar as it was able to capture a particular aspect of the behaviour of the volatility, i.e. the reversion of their asymmetric reaction to news. Empirical evidence from stock market returns in six countries: the United Kingdom, Germany, Japan, the United States, France, Italy, showed that such a model outperformed the traditional asymmetric ARCH equations.

Li (1998) provided tests of multifactor asset pricing model in which time-varying risk premiums were related to the conditional volatility of the market return and economic state variables. He provided new evidence on the relationships between the conditional volatility of the stock markets, the volatility of economic variables and business conditions. Tests rejected the joint hypothesis that the model explained both the cross-sectional and intertemporal variation of expected returns on size or industry portfolios. Furthermore, tests suggested that the rejection was mostly attributed to the inability of the model to explain the dynamic behaviour of expected returns on different size portfolios or on cyclical and non-cyclical industry portfolios.

Kearney (1998) examined the causes of conditional volatility in a small, internationally integrated stock market, using the Irish stock market as example. He related Irish stock market conditional volatility to British stock market conditional volatility and business cycle variables from July 1975 to May 1994. He found that exchange rate volatility was a more significant determinant of volatility in a small, internationally integrated stock market than was interest rate volatility. He supported that a potential benefit of membership in the European Monetary system may reduce stock market volatility in the smaller member countries.

Volatility Persistence

Poterba and Summers (1986) tested the time-series property of volatility. They argued that shocks to volatility have to persist for a very long time in order for the volatility to have significant impact on the stock prices. If shocks to volatility were only transitory, no adjustment of the future discount rate would be made by the market. Thus, expected stock returns were not affected by the volatility movement. *(Hence by empirically rejecting the persistence property using some volatility measures they refused the above claims of Malkiel and Pindyck)*. The volatility measures, that had been used, were monthly averages of daily stock sample variances, and the implied variance of a CBOE index, an ex ante measure. Unit root tests were performed and the existence of unit roots is rejected for both cases. They estimated the serial correlation in the volatility measure, and concluded that shocks to the stock volatility were very short-lived. As a result, using the fundamental valuation formula they obtained a very small estimate for the elasticity of the stock price to volatility shocks.

Pindyck (1986) rejoined this issue by estimating a portfolio choice model. He obtained estimates of the index of relative risk aversion in the range of 3 to 4. While admitting that changes in variance did not persist long, he still claimed that *'they did seem to explain more than other variables (e.g. changes in corporate profits and changes in the real interest rate), because they have been large in magnitude and because the index of risk aversion was large'*. He reported that about one-third of the 1974 market decline could be attributed to volatility changes.

French, Schwert, and Stambaugh (1987) reported the necessity of first-order differencing in order to obtain stationary, although no explicit tests of integration were made. A series of anticipated volatility was obtained from the fitted value of the ARIMA process and it was found to be related weekly with the expected risk premium. On the other hand, strong evidence was found that *'unexpected stock market returns were negatively related to the unexpected volatility of stock price returns'*.

Chou (1988) presented issues of volatility persistence and the changing risk premium in the stock market which was investigated using the GARCH estimation technique. He had got a point of the index of relative risk aversion of

4.5 and confirmed the existence of changing equity premiums in the US during 1962-1985. The persistence of shocks to the stock return volatility was so high that the data could not reject a non-stationary volatility process specification. The results of his study were consistent with Malkiel and Pindyck's hypothesis *that it was the unforeseen rise in the investment uncertainty during 1974 that caused the market to plunge.*

Elyasiani and Mansur (1998) employed the generalised autoregressive conditionally heteroskedastic in mean (GARCH-M) methodology to investigate the effect of interest rate and its volatility on the bank stock return generation process: This framework discarded the restrictive assumptions of linearity, independence, and constant conditional variance in modelling bank stock returns. The model presented allowed for shifts in the volatility equation in response to the changes in monetary policy regime in 1979 and 1982 to be estimated. ARCH, GARCH, and volatility feedback effects were found to be significant. Interest rate and interest rate volatility were found to directly impact the first and the second moments of the bank stock returns distribution, respectively. The latter also affected the risk premia indirectly. The degree of persistence in shocks was substantial for all the three bank portfolios and sensitive to the nature of bank portfolio and the prevailing monetary policy regime.

Volatility Autocorrelation of Returns

An increasing number of empirical studies, starting with Fama (1963, 1965), have shown that time series of financial asset returns tended to be serially uncorrelated over time but not independent. Although it is generally accepted that distributions of stock price returns were leptokurtic and skewed, there was no unanimity regarding the best stochastic return generating model to capture these empirical characteristics.

Approaches to describing the behaviour of stock prices were long dominated by a simple model, a geometric random walk with uncorrelated innovations (Fama, 1970). An implication of this model was that stock returns were independent and identically distributed (i.i.d.) random variables. Early tests found little evidence of economically significant short-horizon autocorrelations and predictability, thereby supporting the weak form of the efficient which specifies that the price histories of stocks contain no useful information on future prices (Fama, 1970). However, later research produced a substantial body of literature challenging the adequacy of this model.

Poterba and Summers (1988) suggested that stock returns showed positive serial correlation over short periods and negative correlation over longer intervals. This conclusion emerged from data on equal-weighted and value-weighted NYSE returns over the 1926-1985 period and corroborated by data from other nations and time periods. Although individual data sets did not consistently

permit rejection of the random-walk hypothesis at high significance levels, the various data sets together strengthened the case against its validity. Their point estimates suggested that transitory price components accounted for a substantial part of the variance in returns.

LeBaron (1992) explored the relationship between serial correlation and volatility for several different stock return series at daily and weekly frequencies. It was found that serial correlation was changing over time and was related to stock return volatility. An extension to the GARCH model was proposed and estimated, revealing parameters consistent with other findings in his study. His result generally indicated that first-order autocorrelations were larger for periods of lower volatility and smaller during periods of higher volatility.

Table 1: Serial Correlation and Volatility for Different Stock Markets

	Return		Series		
	S&P Daily	S&P Weekly	Value Weighted	Dow	IBM
Sample Size	16.736	3.256	6.663	12.756	1.382
Mean*100	0.0180	0.0920	0.0437	0.0310	0.1909
SE*100	1.1531	2.6766	0.8454	0.8292	2.8839
Skewness	-0.4990	-0.4498	-1.4100	-0.3206	0.0000
Excess Kurtosis	22.7914	7.6236	36.7599	6.4550	2.3728
P ₁	0.0618	0.0194	0.1908	-0.0037	0.0081
P ₂	-0.0385	0.0484	-0.0107	-0.0251	-0.0189
P ₃	-0.0031	0.0118	0.0029	0.0228	0.0671
P ₄	0.0304	0.0192	-0.0048	0.0355	-0.0291
P ₅	0.0210	-0.0311	0.0282	0.0454	-0.0133
Bartlett SE	0.0077	0.01752	0.0122	0.0089	0.0269

Note- p₁ refers to the autocorrelation at lag 1; Bartlett refers to the Bartlett standard errors(SE) for the correlations on each series.

S and P Daily Returns: It has a large estimated kurtosis and very small autocorrelations.

S and P Weekly Returns: The serial correlations are very small and with the exemption of P₃, not significantly different from zero. The tests of serial correlation show very little evidence for strong correlations in weekly data.

Booth and Koutmos (1998) modelled index stock returns for four major European stock markets as conditionally heteroskedastic processes with time dependent serial correlation. The evidence suggested that current returns in these markets were non-linearly dependent on their past history. The dependence was strong during calm periods and weak during volatile periods and manifested itself as an inverse relationship between first order autocorrelation and volatility. While this relationship was statistically significant

in daily returns, it was absent from weekly returns. Additional tests revealed that the non-linear specification used by LeBaron (1992) was not necessarily the most adequate representation of the short-term dynamics of stock index returns.

Cao and Tsay (1992) used the absolute value of the mean-corrected excess return to measure the volatility of stock returns. They applied various nonlinearity tests available in the literature to show that such volatility series were strongly non-linear. They then explored the use of threshold autoregressive (TAR) models in describing monthly volatility series. The model built suggested that the volatility series exhibited significant lower-order serial correlations when the volatility was large, indicating certain volatility clustering in stock returns. Out-of-sample forecasts were used to compare the TAR models with linear ARMA models and non-linear GARCH and EGARCH models. Based on mean squared error and average absolute deviation, the comparisons showed that (a) the TAR models consistently outperformed the linear ARMA models in multi-step ahead forecasts for large stocks, (b) the TAR models provided better forecasts than the GARCH and EGARCH models also for the volatility of large stock returns, (c) the EGARCH model gave the best long-horizon volatility forecasts for small stock returns.

Ghosh (1992) supported that previous studies showed that heteroskedasticity and serial correlation were present in the market model. In his study, he estimated market model parameters under a general error structure (GARCH). Employing daily stock rate of returns data obtained from CRSP for 1985 through 1989, excluding October 1987 and October 1989, he showed that conditional heteroskedasticity and serial correlation were widespread. Evidence showed that small firms apparently had lower betas than large firms. He offered an alternative method for estimating betas of individual stocks and portfolios based on GARCH processes.

Brown, Harlow, and Tinic (1993) presented empirical evidence demonstrating that the risk and expected returns of common stocks typically changed in the aftermath of large price movements. When temporary changes in uncertainty followed major financial events, subsequent stock returns should be positively correlated with the shift in return volatility. This prediction was strongly supported by the data on more than 9,100 daily price change events during 1962-1985. Moreover, the data also suggested that ex ante returns on common stocks might incorporate a premium in parameter uncertainty associated with the events.

Brorsen and Yang (1994) proposed three alternative models of daily stock index returns: (1) a diffusion-jump process; (2) an extended generalised autoregressive conditional heteroskedasticity (GARCH) process; and (3) a combination of the GARCH and jump processes. Non-nested tests between the diffusion-jump process and a GARCH(1,1) process with t-distributed errors rejected the diffusion-jump process, but did not however reject the GARCH process.

Kolmogorov-Smirnov tests of fit, however, rejected the GARCH(1,1)-t process for all cases. Non-linear dependence was not removed for the value-weighted index and the S and P 500 stock index; therefore, deterministic chaos could not be dismissed.

Richardson and Smith (1994) provided unified approach for testing serial correlation in stock returns. They described a general class of statistics which were linear combinations of consistent estimates of autocorrelations and then provided a common perspective on the asymptotic distribution and power of these statistics. They showed that: a. many of the test statistics for serial correlation were highly correlated under the null of a random walk. From the random walk perspective, therefore, they showed that much of the evidence across these statistics was consistent with sampling error. b. they also provided a comparison of the power properties of currently used test statistics. As a gauge of their potential against mean-reversion alternatives, these statistics compared to the asymptotically most powerful test in their class. For mean-reversion alternatives, among the class of linear combinations of j -order autocorrelations, their results suggested that the most powerful tests placed declined weights on the j -order autocorrelations.

Danielson (1998) presented a multivariate stochastic volatility (MSV) model together with an estimation method. Estimation of the MSV model required specialised estimation techniques since the volatility was a dynamic latent variable. The simulated maximum likelihood technique was expanded to allow for estimation of models with multiple latent variables and was applied to the MSV model. The MSV model was compared with a multivariate GARCH model. The MSV model had fewer parameters and higher likelihood values than the multivariate GARCH models. The univariate models were compared with a Monte Carlo experiment where the likelihood domination was confirmed.

Forecasting and Filtering

Scheinkman and LeBaron (1989) supported that the behaviour of the statistics seemed to leave no doubt that past weekly returns help predict future ones even though they are uncorrelated. Furthermore, it seemed that a substantial part of the variation on weekly returns was coming from nonlinearities as opposed to randomness. Or, more moderately, the data were not incompatible with a theory where some of the variation would come from nonlinearities as opposed to randomness and were not compatible with a theory that predicted that the returns were generated by i.i.d. random variables.

Nelson and Foster (1995) developed conditional heteroskedastic process under which a misspecified ARCH model successfully performed tasks, filtering and forecasting. The ARCH model correctly specified the functional form of the first two conditional moments of all state variables. They applied these results to

a diffusion model employed in the options pricing literature, the stochastic model of Hull and White (1987), and Wiggins (1987).

Wiggins (1987) solved the call option valuation problem given a fairly general continuous stochastic process for return volatility. Statistical estimates for volatility process parameters were calculated for several individual stocks and indices. The resulting estimated option values did not differ dramatically from Black-Scholes values in most cases, although there was some evidence that for longer-maturity index options, Black-Scholes overvalued out-of-the-money calls in relation to in-the-money calls.

Pesaran and Timmerman (1995) examined the robustness of the evidence on predictability of US stock returns, and addressed the issue of whether this predictability could have been historically exploited by investors to earn profits in excess of a buy-and-hold strategy in the market index. They found that the predictive power of various economic factors over stock returns changed through time and tended to vary with the volatility of returns. The degree to which stock returns were predictable seemed quite low during the relatively calm markets in the 1960s, but increased to a level where, net of transaction costs, it could have been exploited by investors in the volatile markets of the 1970s.

Haugen and Baker (1995) found that the determinants of the cross-section of expected stock returns were stable in their identity and influenced from period to period and from country to country. Their results suggested that: first, stocks with higher expected and realised rates of returns were unambiguously lower in risk than stocks with lower returns. Second, the important determinants of expected stock returns were strikingly common to major equity markets of the world. *Overall, the results seemed to reveal a major failure in the efficient markets hypothesis.*

Leverage -Interest Rate Effects

Black (1976) noted that volatility tended to grow in reaction to bad news (excess returns lower than expected), and fall in response to good news (excess returns higher than expected). The economic explanation given by Black was that negative (positive) excess returns made the equity value, hence the leverage ratio, of a given firm increased (fell), thus raising (lowering) its risk and the future volatility of its assets. This phenomenon had consequently come to be referred to as the leverage effect (Pagan and Schwert 1990; Campbell and Hentschel, 1992).

Merton (1980) supported that while the expected market return was a number frequently required for the solution of many investment and corporate finance problems, by comparison with other financial variables, there was little research on estimating this expected return. Current practice for estimating the expected market return added the historical average realised excess market returns to the current observed interest rate. While those models explicitly reflected the

dependence of the market return on the interest rate, it failed to account for the effect of changes in the level of market risk. Three models of equilibrium expected market returns which reflected this dependence were analysed. Estimation procedures which incorporated the prior restriction that equilibrium expected excess returns on the market were positive and were derived and applied to return data for the period 1926-1978. The principal conclusions from this exploratory investigation were: (1) in estimating models of the expected market return, the non-negativity restriction of the expected excess return should be explicitly included as part of the specification, and (2) estimators which used realised returns should be adjusted for heteroskedasticity.

Christie (1982) examined the relationship between the variance of equity returns and several explanatory variables. It was found that equity variances had a strong positive association with both financial leverage and, contrary to the predictions of the options literature, interest rates. To a substantial degree, the negative elasticity of variance with respect to value of equity that was part of market folklore was found to be attributable to financial leverage. A maximum likelihood estimator was developed for this elasticity that was substantially more efficient than extant estimation procedures.

Cheung and Ng (1992) showed that after controlling for the effects of bid-ask spreads and trading volume the conditional future volatility of equity returns was negatively related to the leverage of stock price. This 'leverage effect' was stronger for small, as compared to large, firms. They also documented that while the essential characteristics of the relationship between stock price dynamics and firm size were stable, the strengths of the relationships appeared to change over time.

Jones, Kaul, and Lipson (1994) examined the effects of trading and information flows on the short-run behaviour of stock prices by comparing the behaviour of stock return volatility during trading and non-trading periods. They defined non-trading periods as periods when exchanges and business were open but traders endogenously chose not to trade. After correcting for the bid/ask bounce and stickiness in quotes, they found that a large proportion of daily stock return volatility occurred without traders, especially for large firms. Furthermore, they provided new evidence that public (versus private) information was the major source of short-term return volatility.

Braun, Nelson, and Sunier (1995) investigated the conditional covariance of stock returns using bivariate exponential ARCH (EGARCH) models. These models allowed market volatility, portfolio specific volatility, and beta to respond asymmetrically to positive and negative market and portfolio returns and 'leverage' effects using monthly data. They found strong evidence of conditional heteroskedasticity in both market and non-market components of returns, and weaker evidence of time-varying conditional betas. Surprisingly while leverage effects appeared strong in the market component of volatility,

they were absent in conditional betas and weak and/or inconsistent in non-market sources of risk.

Duffee (1995) found that the statistical relation of individual firms' stock return volatility rises after stock prices fall, was largely due to a positive contemporaneous relationship between firm stock returns and firm stock return volatility. This positive relationship was strongest for both small firms and firms with little financial leverage. However, at the aggregate level, the sign of this contemporaneous relationship was reversed. He concluded that the leverage effect (although it may exist) could not explain the observed relationship between returns and changes in volatility.

Volume versus GARCH Effects

Lamoureux and Lastrapes (1990) provided empirical support for the hypothesis that ARCH was a manifestation of the daily time dependence in the rate of information arrival to the market for individual stocks. Thus, this form of heteroskedasticity was an artefact of the arbitrary, albeit natural, choice of observation frequency. Using daily trading volume as proxy for the mixing variable (daily information arrival), they showed that, for a sample of 20 common stocks, ARCH effects vanished when volume was influenced as an explanatory variable in the conditional variance equation.

Mcleay, Asimakopoulos, and Siriopoulos (1997) examined the information content of volume in the Greek banking sector following the suggestions made by Lamoureux and Lastrapes (1990) that GARCH effects disappeared when volume of trade was included into the conditional variance equation. Their result suggested that the inclusion of volume into the variance equation did not eliminate the GARCH effects but it led to lower volatility persistence.

Omran and McKenzie (1995) extended the results of Lamoureux and Lastrapes (1990) to the U.K. stock market, and examined, in particular, their finding that GARCH modelling captures the serial dependence in volume of trade. Using data on 57 U.K. companies, they found that although the parameter estimates of the GARCH model became insignificant when volume of trade was used in the conditional variance of price changes, the autocorrelations of the squared residuals still exhibited a highly significant GARCH pattern. They argued that the serial dependence in volume of trade explained some but not all of the volatility persistence effects of the GARCH model. Furthermore, the uncorrelated component of volume of trade had a significant impact on the conditional variance of price changes. This could be attributed to the strong association in the timing of innovation outliers in the price changes and unexpected volume.

Sharma, Mougoue, and Kamath (1996) tested for the Generalised Autoregressive Conditional heteroskedasticity (GARCH) effects in stock market indicator returns using NYSE daily return and volume data for four years. The

findings strongly suggested that the market indicator returns were best described by the GARCH model in the absence of volume as a mixing variable. The inconclusion of volume as a proxy for information arrival in the conditional variance model helped in explaining the GARCH effects in stock returns, however, the GARCH effects did not completely vanish.

Jacobs and Onocchie (1998) found that there was a positive relationship between trading volume and price volatility, as measured by the conditional heteroskedasticity of price change in international financial futures markets. Additionally, they documented new statistically significant findings of positive contemporaneous and time varying correlation between price changes and volume, negative time varying risk premia in futures returns, and a monotonically declining and asymmetric effect of innovations on price volatility.

Future Markets: Effects on the Dynamics of Stock Markets

The issue of the impact of futures trading on stock market volatility has received considerable and increasing attention in recent years, particularly following the stock market crash of October 1987. There was little agreement as to the effect futures contracts had on the underlying market. Traditionally, increased volatility, following the onset of futures trading, had been viewed as an undesirable consequence of destabilising forces. This view gained impetus following the stock market crash, which some commentators blamed on futures trading, in general, and program trading, in particular. The impact of destabilising forces could lead to an increase in uncertainty in the spot markets, which, in turn, could raise the required rate of return of investors in the markets. If this is correct the cost of equity capital will be increased, perhaps unduly, leading to a misallocation of resources in the economy. On the other hand, some commentators argue that futures markets provided a mean by which the mechanism for the transmission of news was improved, leading to a more rapid impounding of information in prices and, hence, more volatility.

Merville and Pieptea (1989) proposed and tested empirically a new theoretical model for the volatility of stock-price movements. Using call option prices on 25 stocks and the S and P 500 stock-index futures contract, they found that volatility followed a mixed mean-reverting diffusion process with discrete white noise. The instantaneous elastic force pulled the volatility back to its long-term value. The findings suggested that the Black and Scholes constant-volatility assumption did not hold perfectly.

Baldauf and Santoni (1991) examined the hypothesis that program trading resulted in greater price volatility in the cash market of stocks. The data examined rejected this hypothesis. They tested the presence of ARCH effects in daily stock price returns, controlling for these effects by modelling them, and determined whether the estimated parameters of the model shifted subsequent

to the institution of program trading. No evidence was found of a shift in the model's parameters. This is in accordance with most previous work on this issue. In addition, because the model employed explicitly accounted for ARCH effects, the finding was not subject to a criticism that it was a fortuitous result produced by heteroskedasticity.

Najand and Yung (1991) used a GARCH model to reinvestigate the relationship between volume and price variability in Treasury-bond futures markets. The GARCH specification was found to be more appropriate than standard statistical models because it was consistent with a return distribution which was leptokurtic, and it was also allowed for a long-term memory in the variance of the conditional return distributions.

Merton (1995) argued that the introduction of futures trading and derivative markets, in general, could improve efficiency to information. Therefore, to fully understand the impact of futures trading on stock market volatility and whether any impact was undesirable, it was necessary to understand and take account of the causes of volatility. This, in turn, required an understanding of the causes of the empirically observed phenomena of volatility clustering and the asymmetric response of volatility to news.

Kang and Brorsen (1995) introduced an asymmetric GARCH model that captured asymmetries in the mean equation and determined the most likely distribution of Kansas city wheat futures price changes among alternative conditional heteroskedasticity models. The asymmetric GARCH (2,1)-t with two lags of the conditional variance and one lag of the squared residuals, which considered asymmetry in the mean equation, was selected as the most likely model of Kansas city wheat futures price changes. The alternative models considered were the GARCH-t, the EGARCH-t, and the asymmetric EGARCH-t models. Their results suggested that actual trading returns with the GARCH (OPM) were slightly higher than those with Black's OPM, but the differences were not statistically significant. Most trading returns based on both option trading models (GARCH and Black's) were not significantly different from zero.

Park and Switzer (1995) used the time-dependent conditional variance models such as the Generalised Autoregressive conditional heteroskedastic (GARCH) framework in order to estimate the optimal or minimum risk hedges with futures contracts. Recent studies found that the time-dependent conditional variance model improved the hedging performance in various futures contracts. However, no study had shown the economic viability of the GARCH hedging method with stock index futures in the presence of transactions costs. This study examined two of the most heavily traded stock index futures contracts in the U.S. and Canada: the S & P 500 index futures and Toronto 35 index futures. They found that the GARCH model gave an improved hedging strategy even after accounting for transaction costs.

Abhyankar (1995) supported that during the period 1986 to 1990 there was a strong contemporaneous relationship between the FT-SE 100 futures and cash markets. However, in periods of 'good' news, neither market seemed to lead the other; whereas during times of 'moderate' news, the futures led the cash consistently. During periods of 'bad' news, no consistent pattern in the lead-lag relationship emerged. It was shown also that the futures returns led the cash during times of high volatility, but there was no clear pattern during periods of low volatility. In addition, the futures largely led the cash during periods of high and low trading volume in the underlying equity market. The tests for lead-lag in the conditional volatility suggested that there was no pattern of one market leading the other in terms of volatility.

Antoniou and Holmes (1995) examined the impact of futures trading on the FTSE-100 stock index, following its introduction in May 1984, utilising the Generalised Autoregressive Conditional Heteroskedastic (GARCH) family of statistical techniques. These techniques avoided methodological problems encountered in previous studies and enabled the link between information and volatility to be examined. Their results suggested that futures trading led to increased volatility, but that the nature of volatility did not change post-futures. The finding of price changes being integrated pre-futures, but being stationary post-futures, implied that the introduction of futures had improved the speed and quality of information flowing to the spot market. This was confirmed by the increase in the news of the specific coefficient of the GARCH equation and the reduction in the persistence specified coefficient.

The study of Wilson, Aggarwal, and Inclan (1996) found that when sudden changes in the variance were incorporated directly into an ARCH/GARCH analysis, the persistence of variance decreased dramatically. Hogan, Kroner, and Sultan (1997) examined trading and volatility in the S & P 500 cash and future markets. First, it was examined the effects of program trading simultaneously on the stock and futures markets. Second, the GARCH model allowed the joint distribution of stock and futures returns to vary over time as a function of the information set. Finally, the impact of program trading on volatility in each market was examined by including program trading in the relevant information set. Their results demonstrated that a dramatically different relationship between buy-program trades and volatility than the relationship between sell trades and volatility.

Chatrath and Song (1998) examined the intraday behaviour of the Japanese yen spot and futures rates following news releases and investigated the role of information in the relationship between the volatility in futures and spot markets. The results suggested that *'the evidence of one market leading to greater volatility in the other was at least partly driven by information. The implication was that empirical evidence that future markets caused spot market volatility may be a reflection of futures markets'* reacting more efficiently to new information. This in turn implied

that regulation or elimination of futures market would not necessarily resulted in lower volatility in the spot market.

Antoniou, Holmes, and Priestley (1998) examined the impact of futures trading on stock market volatility. In doing so it extended the traditional analysis of examining whether futures trading had increased stock market volatility by considering the issue of volatility, asymmetries, and market dynamics. The result suggested that although the onset of futures trading had limited impact on the level of stock market volatility over a 3-year period, it had a major effect on the dynamics of the stock market. *The view that market turbulence resulted from the introduction of derivative trading generally appeared unfounded.*

CONCLUSION

Table 2: The most important findings

Conditional Heteroskedasticity	Assumptions
Engle(1982)	Emphases on one period forecast variance with respect to recent past information ARCH process important It allows the conditional variance to change over time, proposed the GARCH model Emphases on drawbacks of GARCH model: a. negative returns between current returns and future volatility, b. Restrict the dynamics of the conditional variance, and c. Does not show persistence of shocks to conditional variance. He proposed the EGARCH model.
Bollerslev(1986)	
Nelson(1991)	
Autocorrelation	
LeBaron(1992)	First order autocorrelations are larger for periods of lower volatility and smaller during periods of higher volatility.
Volatility Persistence	
Poterba and Summers(1986)	Shocks to the stock volatility are short-lived.
French, Schwert and Stambaugh(1987)	Unexpected stock market returns were negatively related to the unexpected volatility of the stock returns.
Leverage Effect	
Duffee(1995)	Leverage effect could not explain (although it may exist) the observed relationship between returns and changes in volatility.
Volume versus GARCH effects	
Lamoureux and Lastrapes(1990)	ARCH effects vanish when volume influences the conditional variance.
Criticism	It does not hold for all markets(i.e. Greek stock market)
Forecasting	
LeBaron(1989)	Past weekly returns help the prediction of future ones, even

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Abhyakar(1995)

though they are uncorrelated.

The tests for lead-lag in the conditional volatility suggest that there is no pattern of one market leading the other in terms of volatility.

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