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Evidence of an asymmetry in the relationship between volatility and autocorrelation

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Abstract

This paper focuses on the general determinants of autocorrelation and the relationship between autocorrelation and volatility in particular. Using UK stock market index and individual stock price data, a multivariate generalized autoregressive conditional heteroskedasticity (M-GARCH) model is used to generate estimates of conditional autocorrelation. The covariance equation of this model is modified to include the potential determinants of autocorrelation including volatility, which is proxied using the time series of filtered probabilities of a Markov regime switching model. Consistent with the previous literature, this paper documents a negative relationship between volatility and autocorrelation. The results suggest that an asymmetry exists in this relationship which is attributed to the constraints placed on short selling.

JEL classification: G12
Keywords: Feedback trading; Conditional autocorrelations; Markov models

1. Introduction

Despite the efforts of academic researchers, identifying the determinants of serial correlation in share prices has proven to be an elusive goal. Fama (1971) attributed the presence of autocorrelation to changes in the risk premia while Fischer (1966) and Scholes and Williams (1977) focused on explanations related to thin trading. The empirical evidence however,

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suggests that actual autocorrelation estimates are significantly greater than those implied by either of these factors (see Atchison, Butler, & Simonds, 1987; Conrad & Kaul, 1988; Lo & MacKinlay, 1988, 1990; Ogden, 1997).

More recently, the presence of autocorrelation has been linked to the activities of "feedback" traders (see Sentana & Wadhwani, 1992). Recognizing the existence of both positive and negative feedback traders in the market, the observed level of autocorrelation at any given point in time is a function of the relative strength of these two different classes of traders. Over time, this relative strength will change and with it, the level of autocorrelation. For example, the arguments of Black (1988, 1989) suggest that a positive relationship exists between volatility and the extent to which rational investors pursue positive feedback trading. As autocorrelation is argued to reflect the activity of feedback traders, changes in volatility therefore have implications for the level of autocorrelation. Where negative return autocorrelation exists, volatility increases should serve to heighten the observed level of autocorrelation. On the other hand, where positive autocorrelation is evident, a rise in volatility should lessen the level of return autocorrelation. In support of this theory, a negative relationship between volatility and autocorrelation has been found in the literature (see inter alia Koutmos, 1997; McKenzie & Faff, 2003; Sentana & Wadhwani, 1992).

In testing the nature of the relationship between volatility and autocorrelation, the previous literature has failed to recognise that heightened volatility may result from either an increase or a decrease in prices. In this paper, we argue this to be an important distinction. To understand why, recall that positive feedback traders tend to follow market trends and buy (sell) in a rising (falling) market. Many stock markets, however, have placed outright bans on short trading or imposed regulations which make short trading unfeasible.[2] In those markets where short trading is allowed, it is typically subject to some form of regulation (such as up-tick and vesting rules) which adds to the cost of trading. Short positions are also frequently closely monitored by the exchange which inhibits the ability of an investor to trade where they wish to remain anonymous. Equivalent restrictions on long positions do not exist.

The restrictions which apply to short trading will curtail the ability of an investor to engage in positive feedback trading following an increase in volatility caused by a fall in prices. No such equivalent restrictions exist to curb the ability of an investor to engage in feedback trading following a volatility shift caused by a rise in prices. In the extreme case of a short trading ban, no positive feedback trading will take place following a volatility increase caused by a fall in prices. In this case, there will be no observable change in autocorrelation as there is no trading response to the volatility shift. Where restrictions on short sales exist, the trading response to a rise in volatility will be less when compared to the trading response following an equivalent increase in volatility caused by a rise in prices. Thus, the change in the observed level of autocorrelation following a rise in volatility will be less where prices are falling compared to where prices are rising.

The restrictions imposed on short selling suggest the presence of an asymmetry in the relationship between volatility and autocorrelation. While our hypothesis applies equally to any stock market with restrictions on short selling, in this paper we will test our hypothesis using data sampled from the London Stock Exchange (LSE). While the UK does not have any regulations that are specifically designed to restrict short selling, its practice is limited to only a

[2] For a survey of short selling arrangements in stock markets around the world see Bris, Goetzmann, and Zhu (2003) and Charoenrook and Daouk (2005).

small number of professional investors.[3] Establishing a short position involves a complex and costly transaction process, which generally requires the investor to secure vesting rights over the stock. Further, the UK government has specific taxation rules that apply to stock lending in equities. These practical limitations on short selling mean that it is more difficult and less profitable for investors to engage in feedback trading when the market is falling.

Our use of individual stock data sampled from the LSE contrasts with much of the previous literature which has focused on the US experience. These two markets operate under a very different trading systems as the NYSE is a quote-driven market in which market makers take the opposite side of every transaction. The LSE, however, is primarily an order-driven market in which the public trades with each other via a centralized exchange. Madhavan (2000) provides a concise survey of these differences and their implications for market outcomes. It is not necessarily obvious that the lessons learned in one market can be assumed to apply to the other. Thus, the use of LSE data in this paper allows us to provide empirical evidence on the determinants of autocorrelation for a different trading system to that which has been the focus of the previous literature.

One further contribution of our paper relates to the model we employ to test our hypothesis. A multivariate generalized autoregressive conditional heteroskedasticity (M-GARCH) model is specified in which the covariance equation contains a conditional autocorrelation variable that is a function of a number of factors including volatility, among others, which is proxied using a Markov switching model. As such, this paper overcomes a potential endogeneity problem that has hampered previous studies in which the conditional variance from the GARCH model was used to generate the conditional autocorrelation series as well as to proxy for volatility (see McKenzie & Faff, 2003).

The remainder of this paper is presented as follows. Section 2 details the M-GARCH model used to test the nature of the relationship between autocorrelation and its determinants. The regime switching model that is used to generate the estimates of volatility for each stock is presented in Section 3. Section 4 introduces and describes the data to be tested. Following this discussion, M-GARCH model estimates are presented and the hypothesised asymmetric relationship between volatility and autocorrelation considered. Finally, Section 5 provides some concluding comments to our paper and summarises our findings.

2. Multivariate GARCH model estimates of conditional autocorrelation

Empirical estimates reveal that stock return autocorrelation is sample dependent and may exhibit sign reversals (see Chan, 1993; Knif, Pynnönen, & Luoma, 1996) which suggests that it is appropriate to model autocorrelation as a time-varying process. Following this lead, Sentana and Wadhwani (1992), Koutmos (1997) and Booth and Koutmos (1998) generated conditional autocorrelation estimates whose temporal variation was driven solely by changes to the variance. One weakness of this model is the assumption of a constant covariance which potentially suppresses an important source of variation in autocorrelation. In this paper, conditional autocorrelation estimates are generated using an M-GARCH model in which both the variance and covariance equations are time varying. Estimates of conditional autocorrelation may be generated where this M-GARCH model is fitted to that returns series (R_{1t}) as well as its one day lagged values (R_{2t}).

[3] For complete details on short selling in the UK see Financial Services Authority (2002).

Specifically, the mean equation for each series is specified with a constant as well as day-of-the-week dummies, i.e.:

$$\begin{aligned} R_{1t} &= \alpha_{1c} + \sum_{i=\text{Mon}}^{\text{Thu}} \alpha_{1i} \cdot \text{DayDum}_{it} + e_{1t} \\ R_{2t} &= \alpha_{2c} + \sum_{i=\text{Mon}}^{\text{Thu}} \alpha_{2i} \cdot \text{DayDum}_{it-1} + e_{2t} \end{aligned} \tag{1}$$

where R is the continuously compounding return on a stock (or index), calculated as log price relative $\times$ 100, and DayDum_{it} is the dummy variable capturing daily periodicity, where i = Mon, Tue, Wed and Thu. The error terms (e_{1t}, e_{2t}) are assumed to be normally distributed with a mean of zero and a conditional variance which is modeled as a GARCH process which has been modified to include a threshold term and day of the week dummy variables, i.e.:

$$\begin{aligned} h_{R1,t} &= \beta_{1c} + \beta_{1h} \cdot h_{1,t-1} + \beta_{e11} \cdot e^2_{1,t-1} + \beta_{e12} \cdot e^2_{1,t-1} \cdot I_{1t} + \sum_{i=\text{Mon}}^{\text{Thu}} \beta_{1i} . \text{DayDum}_{it} \\ h_{R2,t} &= \beta_{2c} + \beta_{2h} \cdot h_{2,t-1} + \beta_{e21} \cdot e^2_{2,t-1} + \beta_{e22} \cdot e^2_{2,t-1} \cdot I_{2t} + \sum_{i=\text{Mon}}^{\text{Thu}} \beta_{2i} . \text{DayDum}_{it-1} \end{aligned} \tag{2}$$

where I_{1t} is an indicator variable that takes one where $e_{1t-1} < 0$, and zero otherwise. I_{2t} is similarly defined for e_{2t-1}. This threshold term is designed to capture the asymmetric nature of volatility responses to positive and negative shocks to the market (see Bollerslev, Engle, & Nelson, 1994). This approach to modeling variance asymmetry is first introduced in Glosten, Jagannathan, and Runkle (1993) and is referred to as GJR. In addition, Exponential GARCH (EGARCH) specifications were also tested. The results are qualitatively unchanged to those obtained using a GJR model and are available on request.

In addition to the variance equations, the covariance equation also needs to be specified and as has already been discussed, a conditional specification is adopted in which all elements are time varying:

$$h_{R1,R2,t} = \rho_t \cdot \sqrt{h_{R1,t} \times h_{R2,t}} \tag{3}$$

where ρ_t is the conditional return autocorrelations of an individual stock (or an Index) which is specified as:

$$\rho_t = d_0 + d_1 \cdot \rho_{t-1} + d_2 \cdot (e_{1t-1} \cdot e_{2t-1}) / \sqrt{h_{R1t-1} \times h_{R2t-1}}. \tag{4}$$

The focus of this paper is on identifying the determinants of autocorrelation and as such, Eq. (4) may be augmented to include these variables, i.e.

$$\begin{aligned} \rho_t = {} & d_0 + d_1 \cdot \rho_{t-1} + d_2 \cdot \left(e_{1t-1} \cdot e_{2,t-1}\right) / \sqrt{h_{R1,t-1} \times h_{R2,t-1}} + c_1 \cdot \text{MRP3}_{t-1} \\ & + c_{12} \cdot \text{MRP4}_{t-1} + c_2 \cdot \text{AAP}_{t-1} + c_3 \cdot \text{AAN}_{t-1} + c_4 \cdot \text{LVM}_{t-1} + c_5 \cdot \text{EcoCycle}_{t-1} \\ & + \sum_{i=\text{Mon}}^{\text{Thu}} c_i \cdot \text{DayDum}_t \end{aligned} \tag{5}$$

where $\mathrm{MRP3}_{t-1}$ ($\mathrm{MRP4}_{t-1}$) is the time series of filtered Markov regime probabilities of return regime 3 (4) which corresponds to a negative (positive) return and high return volatility. These terms and their derivation are explained more fully in Section 3. AAP_{t-1} (AAN_{t-1}) is a dummy variable that takes the value one if an above average positive (negative) return occurs. LVM_{t-1} is the natural log of traded volume of stock or the index. Finally, $\mathrm{EcoCycle}_{t-1}$ is the economic cycle dummy that takes the value of one if business cycle is on a downward path, and zero otherwise. By augmenting the autocorrelation equation in this way, this paper avoids the two-step estimation procedure of McKenzie and Faff (2003) with resulting gains in estimation efficiency. Further, the use of Markov probabilities avoids the issue of endogeneity that occurs when the volatility proxy and the autocorrelation series are not independent.[4]

The arguments of Black (1988, 1989) and the empirical evidence of Sentana and Wadhwani (1992), Koutmos (1997), Booth and Koutmos (1998) and McKenzie and Faff (2003) suggest that a negative relationship exists between volatility and autocorrelation. In terms of the model to be tested, c_1 and c_{12} in Eq. (5) are expected to be negative in sign reflecting this relationship. A change in autocorrelation from a given rise in volatility however, is argued to be less where the underlying cause for the change in volatility is falling prices. Recognising this potential asymmetry in the context of the model, we conjecture that the coefficient associated with the high volatility/falling market scenario will be less than the coefficient estimated for the high volatility/rising market scenario, i.e.$|c_1|<|c_{12}|$.

3. Markov regime shifting models of exchange rate volatility

The observed volatility clustering in high frequency return series may be explained by the existence of different regimes with different variances present in the data generating process. These regimes can be modelled as a pure Markov switching variance process (see Kim, Nelson, & Starz, 1998; Turner, Starz, & Nelson, 1989). We use the Markov model of Bollen, Gray, and Whaley (2000) to generate the regime probabilities which are interpreted as a proxy for volatility in that series. In this section, we outline the essential elements of this model and interested readers are directed to the original article for a more detailed discussion of this approach.

The return r in period t is defined as:

$$r_t = \mu_{\mathrm{MSP1},t} + e_t$$

where

$$e_t \sim N\left(0, \sigma^2_{\mathrm{MSP2},t}\right) \tag{6}$$

where, MSP1 is the first order, two state Markov switching process that drives the return and has the transition probability of:

$$\prod_{\mu} \equiv \begin{bmatrix} p_\mu & 1-p_\mu \\ 1-q_\mu & q_\mu \end{bmatrix}. \tag{7}$$

Depending on the state governed by MSP1 the mean return could be either μ_1 (State = 1) or μ_2 (State = 2). The variance of the error term, e_t, is driven by another first

[4] McKenzie and Faff (2003) generated conditional autocorrelation estimates using an M-GARCH model and subsequently tested the relationship between autocorrelation and its determinants in a SUR framework. The conditional variance from this GARCH model was used to proxy volatility and also appeared as the denominator in the autocorrelation estimate.

order, two state independent Markov switching process, MSP2 whose transition probability is:

$$\prod_{\sigma} \equiv \begin{bmatrix} p_\sigma & 1-p_\sigma \\ 1-q_\sigma & q_\sigma \end{bmatrix}. \tag{8}$$

Thus, the variance could be either σ_1^2 (State = 1) or σ_2^2 (State = 2), depending on the state. It is clear from Eq. (6) that the model for the return generating process is conditionally normal and the parameters of the distribution depend on the state under consideration. But the nature of the two independent Markov switching processes suggests that we have four different state combinations to consider. These are {MSP1, MSP2} ≡ {(1,1), (2,1), (1,2), (2,2)}. That is, there are four separate regimes that need to be considered: Regime 1 = low mean (negative return) state and low volatility state; Regime 2 = high mean (positive return) and low volatility; Regime 3 = low mean (negative return) and high volatility; and Regime 4 = high mean (positive return) and high volatility. Using Eqs. (7) and (8), the overall transition probability of the combined process can be written as:

$$\begin{bmatrix} \Pi_\mu \cdot p_\sigma & \Pi_\mu \cdot (1-p_\sigma) \\ \Pi_\mu \cdot (1-q_\sigma) & \Pi_\mu \cdot q_\sigma \end{bmatrix}. \tag{9}$$

Since the return generating process is conditionally normal, it is straightforward to write the conditional density function of the joint process given a state pair (a regime). We multiply the conditional densities for different states by the corresponding probabilities of the states and sum

Table 1
Conditional and unconditional autocorrelation estimate summary

	Code	ρ_i	Mean ρ_{it}	Max ρ_{it}	Min ρ_{it}
FTSE100	FTSE	0.0315*	0.0522	0.1914	−0.1399
Glaxo Smith Kline (GSK)	GSK	0.0345*	0.0801	0.2560	−0.1077
Shell transport and trdg.	SHEL	0.0250	0.0643	0.2219	−0.1254
Barclays	BARC	0.0899*	0.0692	0.3252	−0.1244
Diageo	DGE	0.0320*	0.0986	0.3676	−0.0440
Unilever (UK)	ULVR	0.0537*	0.0573	0.2067	−0.0606
TESCO	TSCO	−0.0174	0.1002	0.3566	−0.0225
Brit. American tobacco	BATS	0.0247	0.0513	0.3119	−0.2267
Rio Tinto	RIO	0.0951*	0.0661	0.4011	−0.3042
Aviva	AV.	0.0222	0.1047	0.3200	−0.1367
Prudential	PRU	0.0195	0.0654	0.2184	−0.0373
Reckitt Benckiser	RB.	0.0398*	0.0663	0.2161	−0.1098
Cadbury Schweppes	CBRY	0.0250	0.0826	0.2898	−0.0781
Marks and Spencer group	MKS	−0.0286	0.0454	0.1241	−0.0893
Legal and general	LGEN	−0.0146	0.0553	0.2217	0.0027
Sainsbury (J)	SBRY	0.0208	0.0532	0.2465	−0.1012
Boots group	BOOT	0.0222	0.0790	0.2291	−0.0536
BOC group	BOC	0.0105	0.0652	0.2407	−0.1581
Allied domecq	LAND	−0.0046	0.0659	0.2164	−0.1056
Dixons gp.	DXNS	0.0472*	0.0767	0.2120	−0.1029
Imperial chemical ind.	ICI	0.0755*	0.0840	0.3000	−0.0666

Note: *Significant at the 5% level.
This table presents unconditional autocorrelation (ρ_i) estimates obtained using the regression equation $r_{i\ t} = \mu_0 + \rho\ r_{i\ t-1} + \varepsilon_t$ for U.K. market and individual stock returns data sampled over the period October 1986 to September 2003. The mean, maximum and minimum conditional autocorrelation (ρ_{it}) estimate generated by a bivariate GARCH model for these same series is provided in the final three columns.

them to obtain the likelihood function. Next, we maximize the weighted likelihood function numerically with respect to the parameters of the model, which are $\Theta \equiv (\mu_1, \sigma_1^2, \mu_2, \sigma_2^2, p_\mu, q_\mu, p_\sigma, q_\sigma)$. This algorithm generates the filtered probabilities of each state, i.e. the probability of a particular state occurring given the information up to that point in time. These are the time series of return/volatility regime probabilities that represent the market participants' view of the state of return/volatility in the individual stock. In this paper, the time series of the resulting probabilities for each of the four regimes are used to explain the time-varying nature of conditional return autocorrelations. As the regime 1 and 2 probabilities, $\mathrm{MRP1}_t$ and $\mathrm{MRP2}_t$, will contain the same information (with opposite sign) as the high volatility regime probabilities (regimes 3 and 4, $\mathrm{MRP3}_t$ and $\mathrm{MRP4}_t$), our model only formally considers the latter as exogenous variables in Eq. (5).

4. Data and results

The data in this study consists of daily price and traded volume data for the FTSE100 market index as well as 20 individual stocks listed on the LSE (details of these stocks are available in the Table 1). These individual stocks collectively represent some of the best known, most keenly followed and most heavily traded shares on the LSE. This bias toward heavily traded stocks is intentional and important as it effectively controls for the induced autocorrelation that comes from thin trading. The data is sampled over a period beginning November 1986 to the end of September 2003 giving a total of 4140 daily observations.[5] A lengthy sample period is chosen to allow a more complete exploration of the dynamic evolution of first order autocorrelation coefficients over time. These data were taken from Datastream and the price series were transformed to approximate continuously compounded returns. The UK business cycle data were obtained from the Economic Cycle Research Institute and indicates recessionary phases for the period May 1990 to March 1992.

4.1. Conditional and unconditional autocorrelation

Unconditional autocorrelation estimates are generated for each of our 20 stocks as well as the index and the results are presented in the third column of Table 1. The market index exhibits significant autocorrelation, 0.0315, as do eight of the individual stocks. The highest observed level of autocorrelation is 0.0951 for Rio Tinto and the lowest significant level of autocorrelation is 0.0320 for Diageo. Of the 12 stocks which did not generate significant autocorrelation, it is possible that a relationship may exist at various points within the sample period and that this information is lost in the averaging process underlying the derivation of these standard estimates. To investigate this further, time-varying autocorrelation estimates are generated using the

[5] A relevant issue given our choice of daily data is whether, as assumed by the theoretical model developed earlier, investors undertake shifts in risk bearing activities on a daily basis. The following comments justify our stance. First, the majority of the technical trading literature focuses on daily decisions made by investors which implicitly assumes that they do modify (or at least act as if they modify) their risk bearing activities to reflect changing conditions in the market on a daily basis. Second, not all investors must update their portfolios every day. Where only a subset of investors update at any point in time, say weekly, and imperfect correlation exists between the trading activities of each subset (such that their trading is spatially distinct), we will be able to observe shifts in risk bearing activities on a continual basis. Third, the bulk of previous literature in this area has also used daily data and for reasons of consistency, the same interval is chosen for analysis in this paper.

M-GARCH model specified in Eqs. (1)–(4). The estimated model coefficients and diagnostic properties of the residuals are not presented to conserve space and are available on request.

The final three columns of Table 1 present a summary of the average conditional autocorrelation estimates as well as the maximum and minimum observed values. The mean conditional autocorrelation for the FTSE index is 0.0522, which is similar to the point estimate. These conditional autocorrelation estimates however, exhibit a good deal of variation and range in value from a maximum of 0.1914 to a minimum of −0.1399. Of the eight stocks that generated significant point estimates of autocorrelation, the mean conditional estimate was higher in every case except for Rio Tinto. Further, all of the average conditional autocorrelation estimates are positive whereas four of the point estimates were negative (although insignificant).

The conditional autocorrelation estimates exhibit a great deal of variation and the largest range of observations was found in the case of Rio Tinto (0.7053) while the smallest range of observations was exhibited by Marks and Spencer Group (0.2133). To gain a better appreciation of the variability of this data, consider a plot of the conditional autocorrelation for Cadbury Schweppes, which is presented in Fig. 1. The plot clearly highlights the variability of autocorrelation and a number of other interesting features can also be identified. From June 1988 until the end of 1997, the autocorrelation varies around the mean value of 0.1255. The equivalent point estimate of autocorrelation estimated over this period is 0.0808, which is significant at 5%. Towards the end of 1997, however, a regime shift is apparent in the data as evidenced by the sudden fall in autocorrelation values. This regime shift could be attributed to the adverse impacts emenating from the 1997 Asian financial crisis. From 1998 until the end of June 2000, the mean conditional autocorrelation is 0.0571, which represents a decline of almost 60%. The equivalent point estimate declines by a similar amount to 0.0358, which is insignificant. A further decline in the conditional autocorrelation series takes place at this juncture and the mean autocorrelation value estimated from July 2000 to the end of the sample period is −0.0085. The unconditional autocorrelation value estimated during this final subperiod is −0.0772, which is significant at 5%. It is reassuring that these shifts in the conditional autocorrelation estimates are mirrored in the unconditional values estimated within each subperiod.

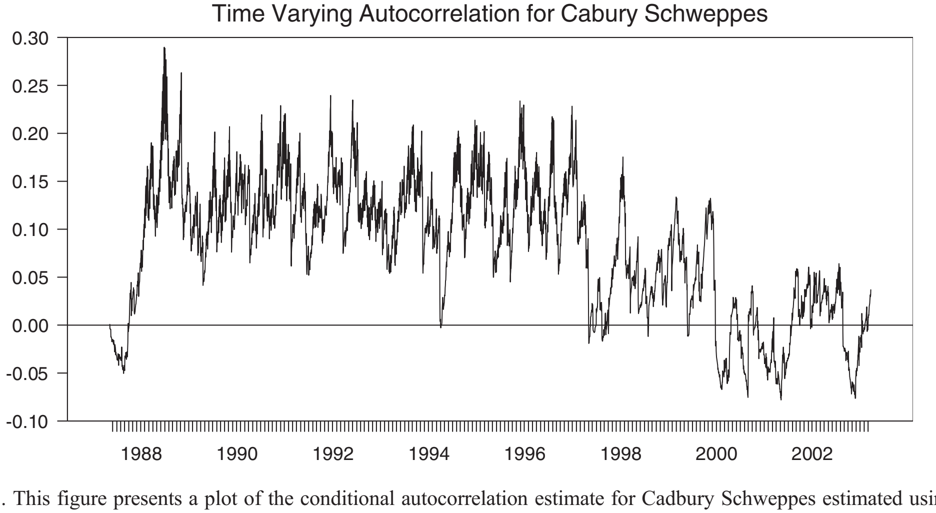

Fig. 1. This figure presents a plot of the conditional autocorrelation estimate for Cadbury Schweppes estimated using a multivariate GARCH model as summarised in Eqs. (1)–(4).

Overall, a comparison of the point estimates of autocorrelation to the average conditional autocorrelation estimate reveals that these two techniques provide a similar degree of information about the general level of observed autocorrelation which is consistent with previous research on US stocks. The unconditional specification, however, omits important information about the variability of autocorrelation and is potentially misleading. For example, the point autocorrelation estimate generated over the entire sample period was insignificant in the case of Cadbury Schweppes. Subperiod analysis however, revealed two distinct periods of significant positive and negative autocorrelation, which were present in the data. This analysis of Cadbury Schweppes is representative of the rest of the sample insomuch as they all exhibited a high degree of variability as well as structural breaks and trends, which were able to be validated using point estimates of the sub-period analysis. It is an interesting empirical issue to consider the extent to which the observed variability in autocorrelation can be explained using economic factors and the remainder of this paper considers this important issue.

4.2. Markov regime switching model estimates of volatility

The literature suggests that one of the primary determinants of autocorrelation is volatility. In this paper, volatility proxies are generated using the Markov regime switching models as detailed in Section 3. Table 2 reports the estimated parameters of the four regime Markov models driven by the two independent Markov switching processes. The mean returns μ_1, μ_2 indicate negative and positive stock returns with respect to the twenty stocks and the FTSE. The transition probabilities P_μ and Q_μ help us infer the persistence of these two different regimes. The high values of P_μ relative to Q_μ, for all the stocks, except for BOC Group and the FTSE, indicate that that the probability of encountering negative return period is very high during the sample period

Table 2
Markov regime switching model estimates

	P_μ	Q_μ	P_σ	Q_σ	σ_1	σ_2	μ_1	μ_2	Log − L
FTSE	0.2423 *	0.9830 **	0.9952 **	0.9763 **	0.5825 **	3.6451 **	−1.5881 **	0.0731 **	6014.36
GSK	0.9533 **	0.2436 **	0.9854 **	0.9637 **	1.2158 **	5.6621 **	−0.0657	1.8464 **	8058.77
SHEL	0.9851 **	0.2915 **	0.9846 **	0.9533 **	1.7303 **	7.5135 **	0.0001	3.1815 **	8612.53
BARC	0.9760 **	0.3947 **	0.9943 **	0.9885 **	0.9348 **	5.3914 **	−0.0300	1.6827 **	7090.99
DGE	0.9818 **	0.2895 **	0.9850 **	0.9702 **	1.4641 **	8.1792 **	−0.0066	2.8015 **	8731.00
ULVR	0.9696 **	0.1443 *	0.9765 **	0.9348 **	1.1070 **	7.5493 **	−0.0337	2.6181 **	8142.94
TSCO	0.9137 **	0.4693 **	0.9802 **	0.9440 **	0.7980 **	6.7859 **	−0.0875	1.0176 **	7527.47
BATS	0.9579 **	0.1902 **	0.9847 **	0.9376 **	1.6960 **	7.5790 **	−0.0677	2.2394 **	8482.75
RIO	0.9586 **	0.1801 *	0.9863 **	0.9366 **	1.5650 **	12.9283 **	−0.0560	2.4939 **	8582.66
AV.	0.9506 **	0.4097 **	0.9843 **	0.9709 **	1.1385 **	7.3774 **	−0.0816	1.7243 **	8460.72
PRU	0.9525 **	0.3229 **	0.9890 **	0.9662 **	1.4484 **	10.3933 **	−0.1169 **	2.2896 **	8674.54
RB.	0.9764 **	0.2542 **	0.9930 **	0.9603 **	2.0667 **	14.7529 **	−0.0474	3.1412 **	8873.49
CBRY	0.9360 **	0.3507 **	0.9673 **	0.8865 **	0.7560 **	8.0498 **	−0.0977 **	1.5665 **	7589.16
MKS	0.9708 **	0.2183 **	0.9682 **	0.8853 **	1.1437 **	7.1358 **	−0.0608 *	2.5816 **	8003.82
LGEN	0.9738 **	0.2784 *	0.9793 **	0.9441 **	1.3564 **	8.0739 **	−0.0601	2.3391 **	8436.19
SBRY	0.9554 **	0.1471	0.9840 **	0.9720 **	1.3918 **	8.4881 **	−0.0476	2.2356 **	8890.99
BOOT	0.9590 **	0.2238 **	0.9815 **	0.9174 **	1.3065 **	8.8848 **	−0.0648	2.2703 **	8155.17
BOC	0.4032	0.9518 **	0.9689 **	0.9069 **	1.1840 **	6.3233 **	−1.2955 **	0.1433	7529.12
LAND	0.9702 **	0.1773 *	0.9825 **	0.9552 **	0.8790 **	6.0048 **	−0.0361	2.1879 **	7644.63
DXNS	0.9627 **	0.2210	0.9720 **	0.9448 **	0.7097 **	3.1913 **	−0.0442	1.4367 **	7041.71
ICI	0.9478 **	0.2768 **	0.9668 **	0.9043 **	1.9008 **	15.4774 **	−0.1591 **	2.7417 **	9572.51

Note : *,**Significant at the 5% and 1% level, respectively.

analyzed. Similarly, the probability of encountering positive return dollar period is quite low. The two estimated variance parameters suggest different levels of variances in the two regimes. The higher variance is bigger by a factor ranging from about three to seven compared to the variance in the low-variance regime. This is similar to results reported in Bollen et al. (2000). The transition probabilities for the variance regimes suggest that in all cases stocks have high propensity to stay in a particular variance regime once it is in that regime. Bollen et al. (2000) explores this particular finding in the context of currency option pricing.

To provide a feel for these regime probabilities, Fig. 2 presents a representative plot of these four regime states for the FTSE where regime 1 = negative returns and low volatility, regime 2 = positive return and low volatility, regime 3 = negative returns and high volatility, and regime 4 = positive returns and high volatility. These probability plots are typical of the Markov model results for each of the stocks included in the sample. These coefficients reveal that the probability of the market being in one of the two low volatility states is high most of the time. Quite sharp and sudden reversals of these probabilities can be seen however, suggesting that these tranquil periods are interspersed with a number of high volatility episodes, which is consistent with the volatility clustering phenomena. For these FTSE probabilities, the correlation between regime 1 and 2 (1 and 4) is -0.2107 (-0.3258) while the correlation between regime 2 and regime 3 (2 and 4) is -0.7277 (-0.7111). The two high volatility regimes exhibit a positive association with a correlation between regime 3 and 4 of 0.6711.

4.3. The determinants of autocorrelation

To test the determinants of autocorrelation, the bivariate GARCH model summarised in Eqs. (1)–(3) and (5) is fitted to the data, where MRP3 and MRP4 correspond to Markov Regime Probability (MRP) 3 and 4, respectively. In addition to volatility, other determinants of autocorrelation are also considered which have been found in the previous literature to be important. These are trading volume, the business cycle, above average returns and the day-of-the-week, which are also included in the autocorrelation equation.

Tables 3 and 4 present the estimated coefficients for the M-GARCH model fitted to the market index as well as the individual stocks. In terms of the ARCH and GARCH coefficients, all of the estimates are significant at 5% except for the GARCH (β_{e11}) term in the model fitted to the returns for BOC, which are significant at 10%. The threshold terms (β_{e12}, β_{e22}) capture the presence of asymmetry in the volatility response to shocks to the market. It is shown that β_{e12} is significant at least at 5% in all cases, whereas β_{e22} is significant in only two cases. Of the day-of-the-week dummy variables in the volatility equation, all were negative and the Monday dummy is significant at 1% for the index. For the individual stocks, the coefficient for the Monday dummy variable, $\beta_{1\mathrm{MON}}$, is negative for 19 of the 20 stocks and 15 of these coefficients were significant at least at 5%. This suggests that volatility on Mondays is significantly less than that typically observed on a Fridays (the omitted case). For the other days of the week, the results are more mixed. The Tuesday coefficient is negative for six stocks and significant in three of those cases while 11 of the 14 positive coefficients were significant. The Wednesday coefficient generated an even mix of ten positive (five significant) and ten negative coefficients (six significant). Two significant and negative coefficients and 18 positive coefficients (17 of which are significant) were generated for the Thursday dummy variable. Overall, there is certainly evidence of day-of-the-week effects in the volatility of these stock returns series. Most notably, Monday and Thursday exhibit clear evidence of lower and higher volatility respectively compared to the base case of Friday.

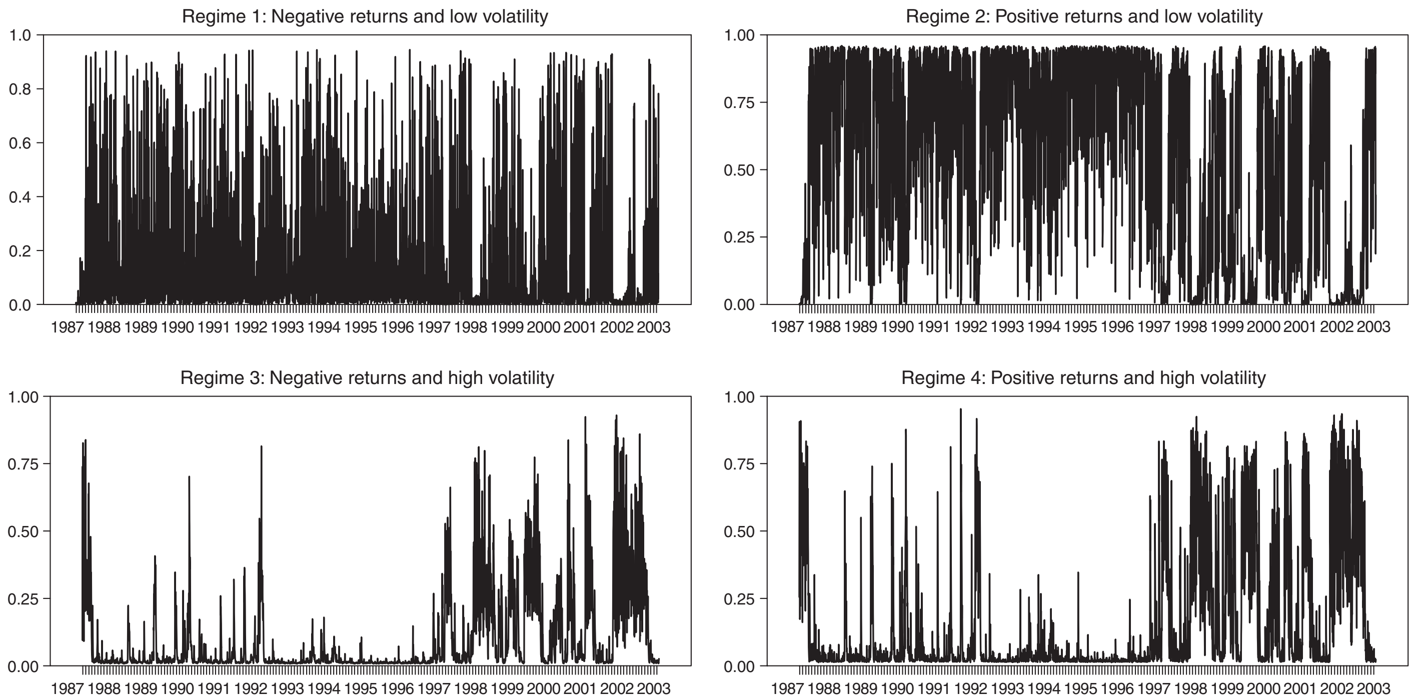

Fig. 2. Markov regime switching probabilities for the FTSE market index.

The last four rows of Panel A of Tables 3 and 4 present the Ljung–Box test of white noise for the estimated standardized residuals, $z_t = e_t/\sqrt{h_t}$. The test results reveal there is evidence of first moment serial correlation but the second moment dependencies are eliminated in most cases. To address any potential concerns over these diagnostics, we tested different functional forms for each of the 21 return series. Specifically, we tested alternative lag structures of the M-GARCH models and the number of lagged dependent variables included in the mean equations, and found that the results of the conditional autocorrelation Eq. (4) estimations remain robust. Thus, we report the results for the parsimonious models and note that any conclusions we draw are not dependent on the model specification.

The arguments of Black (1988, 1989) suggest a negative relationship between volatility and autocorrelation. This relationship has been verified in the empirical literature by papers such as McKenzie and Faff (2003). Changes in volatility, however, may be caused by either rising or falling prices and we argue this to be an important distinction which the previous literature has failed to consider. Our hypothesis is that the change in autocorrelation from a given rise in volatility will be less where the underlying cause for the change in volatility is falling prices due to short sales restrictions. The specification of the covariance equation in the MGARCH model presented in Tables 3 and 4 includes a time-varying autocorrelation coefficient, which is specified as a function of a number of variables. Of primary interest in the current context is the volatility variable, which is proxied by the regime probabilities of the Markov switching model presented in Section 3. Specifically, MRP3 (MRP4) is the time series of filtered Markov regime probabilities of return regime 3 (4) which corresponds to a period of high volatility and negative (positive) returns. The estimated coefficients for c_1 and c_{12} capture the nature of the relationship between autocorrelation and volatility for MRP3 and MRP4, respectively. The estimated results for the FTSE index reveal that the coefficient for c_1 is not significantly different from zero. The estimate for c_{12}, however, is negative and significant. A Wald test of coefficient equality (i.e. $c_1=c_{12}$) is undertaken and the results are presented in the second row of Panel A in Tables 3 and 4. The Wald test coefficient is highly significant rejecting the null hypothesis of equality. For the 20 individual stocks tested, all of the c_1 and c_{12} coefficients are negative and significant. If the analysis is framed in the context of distinguishing between heightened volatility caused by a rise in prices compared to a fall in prices, the absolute value of the c_1 coefficients are less than the absolute value of the c_{12} coefficient in all cases except Rio Tinto, Sainsbury and Marks and Spencer. The Wald test of coefficient equality is rejected at the 5% level or less in 12 cases. Thus, our results are consistent with the previous literature, as these estimation results provide consistent evidence of a negative relationship between autocorrelation and volatility. Distinguishing between the different causes of volatility changes and clear evidence of an asymmetry is found. For over half of our sample, the change in autocorrelation caused by heightened volatility is greater where the underlying cause of the increase in volatility is a rise in prices compared to where the cause is a fall in prices.[6] This asymmetry is argued to be a function of the limitations that are placed on taking short positions. Quite simply, it is more difficult and less profitable for investors to engage in feedback trading when the market is falling. The result is a greater response by feedback traders to volatility increases caused by rising prices compared to falling prices.

[6] As the four regime probabilities sum to one, the low volatility regimes (1 and 2) should have the opposite effect on the dependant variable as the high volatility regimes (3 and 4). In unreported results, we find that the two low volatility coefficients have positive estimates and the estimated coefficient for MP1 > MP2.

Table 3
MGARCH results exploring the determinants of conditional return autocorrelation in the UK market index and individual stocks

	FTSE	GSK	SHEL	BARC	DGE	ULVR	TSCO	BATS	RIO	AV.
α_{1c}	0.0534	0.1127**	0.0302	0.0695**	0.1068**	0.0949**	0.0795**	0.0681*	0.0542	0.1596**
$\alpha_{1\mathrm{MON}}$	−0.0818	−0.0619	0.0075	−0.0245	−0.1367*	0.0132	−0.0558	−0.0579	−0.1032	−0.1407**
$\alpha_{1\mathrm{TUE}}$	0.0092	−0.0118	0.1188*	0.0664	0.0268	−0.0462	−0.0191	0.0239	0.0017	−0.1567**
$\alpha_{1\mathrm{WED}}$	0.0027	−0.0852	0.0185	−0.0714	0.0307	0.0295	0.0054	0.0678	0.0583	−0.1405**
$\alpha_{1\mathrm{THU}}$	−0.0249	−0.0348	0.0647	−0.0969**	−0.0644	0.0105	−0.0084	0.0157	0.0751	−0.0772*
α_{2c}	0.0599**	0.0695**	0.0001	0.0626	0.0909*	0.0794**	0.0256	0.0011	0.0001	0.1290**
$\alpha_{2\mathrm{MON}}$	−0.0866**	−0.0416	0.0505	0.0034	−0.1281	−0.0284	−0.0166	−0.0141	−0.0209	−0.1354
$\alpha_{2\mathrm{TUE}}$	−0.0004	0.0210	0.1293	0.0825	0.0301	−0.0644	0.0178	0.0521	0.0274	−0.1431*
$\alpha_{2\mathrm{WED}}$	0.0038	−0.0646	0.0451	−0.0553	0.0357	0.0194	0.0466	0.0783	0.0928	−0.1045
$\alpha_{2\mathrm{THU}}$	−0.0217	−0.0290	0.0603	−0.0845	−0.1009	−0.0416	0.0316	−0.0030	0.0322	−0.0555
β_{1c}	0.1188**	0.0939**	0.0800**	0.0098**	−0.0276**	0.1328**	0.3803**	0.0033	−0.0368*	−0.0675**
β_{1h}	0.9170**	0.9495**	0.8900**	0.9315**	0.9023**	0.9286**	0.9516**	0.9152**	0.9018**	0.9363**
β_{e11}	0.0686**	0.0522**	0.0728**	0.0452**	0.0807**	0.054**	0.0398**	0.0570**	0.1265**	0.0452**
β_{e12}	0.0021	−0.0154	0.0001	0.0267**	0.0004	0.0005	0.0104	−0.0037	−0.0702**	0.0177
$\beta_{1\mathrm{MON}}$	−0.1899**	−0.5363**	−0.1097**	−0.0191**	−0.4142**	−0.3276	−0.7048**	−0.5901**	−0.0806	−0.2548
$\beta_{1\mathrm{TUE}}$	−0.1139	0.0288	0.1825**	−0.2335**	0.1904**	−0.5161**	−0.3220 *	0.6024**	0.5113**	0.1445**
$\beta_{1\mathrm{WED}}$	−0.1134	−0.1306*	−0.4938**	0.0029	0.0625**	−0.1972	−0.4904**	−0.2435**	−0.4245*	0.3147**
$\beta_{1\mathrm{THU}}$	−0.1108	0.2706**	0.7024**	0.2984**	0.6660**	0.6997**	−0.3224 *	0.7139**	0.6056**	0.2842**
β_{2c}	0.0046**	0.0683	0.1445 *	−0.1724	−0.4735	−0.0792	0.0338**	−0.1387	−0.0713	−0.3755*
β_{2h}	0.9137**	0.9448**	0.9024**	0.9391**	0.9056**	0.9382**	0.9480**	0.9171**	0.9097**	0.9474**
β_{e21}	0.0713**	0.0560**	0.0777**	0.0426**	0.0866**	0.0456**	0.0433**	0.0542**	0.1228**	0.0375**
β_{e22}	0.0015	−0.0147	−0.0114	0.0201	−0.0112	0.0062	0.0108	0.0027	−0.0692	0.0152
$\beta_{2\mathrm{MON}}$	−0.0221	−0.4777	0.1809**	0.3570*	0.5827	0.3268	−0.1784**	0.2006	0.4779	0.5252

$\beta_{2\mathrm{TUE}}$	−0.0074**	0.0450	−0.3191**	−0.1377	0.3436	−0.5789*	−0.0226*	0.0677	−0.1749	0.1674
$\beta_{2\mathrm{WED}}$	0.0161*	−0.0907	−0.0915	0.2401*	0.7403**	0.2241	−0.0897**	0.3797*	0.2021	0.9659**
$\beta_{2\mathrm{THU}}$	0.0617**	0.2865	−0.0193	0.4819**	1.0063*	0.6399*	0.1804**	0.4720	0.1311	0.3343
d_0	0.2922**	0.5105**	0.3983**	0.2359**	0.3995**	0.5323**	0.4288**	0.3151**	0.2227*	0.7574**
d_1	0.7062**	−0.1815*	−0.4939**	−0.3243**	−0.4383**	−0.2578**	−0.4300**	−0.2695**	−0.2207*	−0.3339*
d_2	−0.0240**	−0.0131*	−0.0075	−0.0146	−0.0075	−0.0123*	−0.0079	−0.0263**	−0.0067	−0.0115*
c_1	0.0559	−0.1980**	−0.3869**	−0.0641**	−0.2978**	−0.3832**	−0.3773**	−0.4434**	−0.3643**	−0.2519**
c_{12}	−0.0772**	−0.3076**	−0.7108**	−0.3128**	−0.4973**	−0.6487**	−0.5166**	−0.6129**	−0.3304**	−0.4140**
c_2	0.0299	−0.1441**	−0.1152**	−0.0224	−0.0960**	−0.2456**	−0.1638**	−0.1967**	−0.2219**	−0.0646**
c_3	0.0150	−0.0751**	−0.1122**	−0.0423	−0.0658	−0.2062**	−0.1538**	−0.1614**	−0.2358**	−0.0568*
c_4	−0.0172**	−0.0124**	0.0145*	0.0036**	0.0111*	0.0207**	0.0257**	0.0285**	0.0329**	−0.0304**
c_5	−0.0327	0.0580	−0.0816**	0.1321**	−0.0126	0.0927**	−0.0950*	0.1055**	−0.0501	−0.0130
c_{MON}	0.0190	−0.0339	0.0459	−0.0530	−0.0284	−0.0215	−0.0253	−0.1267**	0.0263	−0.0923*
c_{TUE}	−0.1634**	−0.0946*	0.0671	−0.1439**	−0.0503	−0.0786*	−0.0279	−0.0233	0.0475	−0.1352**
c_{WED}	−0.0294	−0.0717	0.0101	−0.0942*	−0.0186	−0.1516**	−0.0295	−0.0748**	−0.0606	−0.0925**
c_{THU}	−0.0935*	−0.0194	−0.0292	−0.0810*	−0.0237	−0.1309**	−0.0711*	−0.0582	−0.0700	−0.0646*
Panel A										
$\mathrm{Log}-L$	−3461	−7380	−8691	−6562	−8894	−7794	−6384	−8402	−8990	−8154
H0: $c_1=c_{12}$	7.0269**	2.9119	25.2706**	20.3286**	10.2994**	72.9020**	3.3570	4.1672*	0.2577	4.2202*
LB Q(20)[(1)]	31.5024*	62.6097**	43.8194**	45.5842**	62.2461**	50.3480**	55.8600**	44.0278**	25.3144	61.3345**
LB Q^2(20)[(2)]	42.0350**	17.3516	28.0487	25.2980	25.1413	11.8170	27.9418	30.6175	4.4231	37.6244**

Note : *,**Significant at the 5% and 1% level, respectively.

[(1), (2)]Ljung–Box test of white noise (of up to 20 lags) for the estimated standardized residuals from the model, $z_t = e_t/\sqrt{h_t}$ and squared $(z_t)^2$, respectively.

Table 4
MGARCH results exploring the determinants of conditional return autocorrelation in UK stocks

	PRU	RB.	CBRY	MKS	LGEN	SBRY	BOOT	BOC	LAND	DXNS	ICI
α_{1c}	0.0892**	0.1198**	0.0630	0.0918*	0.0679**	0.1281**	0.0551**	0.1078**	0.0663	−0.0247	0.0987**
$\alpha_{1\mathrm{MON}}$	−0.1622**	−0.1741**	−0.0966	−0.1303**	−0.0795	−0.1360*	−0.0666	−0.0767	−0.0840	0.0201	−0.0471
$\alpha_{1\mathrm{TUE}}$	0.0215	0.0017	0.0264	−0.0542	−0.0696	−0.0430	0.0374	−0.1051*	−0.0616	0.1087**	−0.0849
$\alpha_{1\mathrm{WED}}$	−0.1040*	−0.0752	0.0625	−0.0514	0.0017	−0.0788	0.0366	−0.0464	−0.0180	0.1238**	0.0340
$\alpha_{1\mathrm{THU}}$	0.0379	0.0763	0.0645	−0.0715	−0.0679	0.0244	−0.0218	0.0279	−0.0265	0.0419	−0.1147
α_{2c}	0.0622*	0.0692	−0.0587**	0.0133	0.0927	0.0392	0.0069	0.1175*	0.0475	−0.0629	0.0809**
$\alpha_{2\mathrm{MON}}$	−0.1341**	−0.1352	0.0032	−0.0829	−0.1220	−0.0813	−0.0519	−0.0236	−0.0846*	0.0392	−0.1288**
$\alpha_{2\mathrm{TUE}}$	0.0240	0.0223	0.0944*	−0.0016	−0.1226*	0.0025	0.0470	−0.0067	−0.0141	0.1217*	0.0504
$\alpha_{2\mathrm{WED}}$	−0.1027	−0.0529	0.1104*	−0.0182	−0.0431	−0.0063	0.0347	−0.0013	−0.0045	0.1253*	−0.0211
$\alpha_{2\mathrm{THU}}$	0.0317	0.0564	0.0587	−0.0776	−0.1256*	0.0346	−0.0720	0.0226	−0.0474	0.0117	−0.0574
β_{1c}	0.0902**	0.1277**	0.0026	0.0152**	−0.1868	0.0906	−0.0082**	0.0296*	−0.0806**	0.0623**	2.4108**
β_{1h}	0.9141**	0.8810**	0.9438**	0.9012**	0.9343**	0.9377**	0.9459**	0.9427**	0.9088**	0.9148**	0.4261**
β_{1e11}	0.0577**	0.0994**	0.0498**	0.0528**	0.0495*	0.0492**	0.0401**	0.0344	0.0708**	0.0581**	0.3532**
β_{1e12}	0.0288*	−0.0119**	−0.0031	0.0288**	0.0150	0.0086	0.0066*	0.0109	0.0129	−0.0043	−0.0651**
$\beta_{1\mathrm{MON}}$	−0.4982**	−0.6094**	−0.1859**	−0.4202**	−0.3806	−0.6471*	−0.4894**	−0.3439*	0.0811*	−0.1585**	−1.7957**
$\beta_{1\mathrm{TUE}}$	0.0614**	−0.1308	0.0213	0.1351**	0.8351**	−0.0661	0.0815**	0.1155	0.4104**	−0.0309	0.9785**
$\beta_{1\mathrm{WED}}$	−0.0037	0.0813	0.0140	0.2109**	0.0770	−0.2654	0.1110**	−0.0879	−0.3146**	0.0634	2.2855**
$\beta_{1\mathrm{THU}}$	0.2772**	0.6042**	0.3326**	0.5006**	0.5848*	0.7551*	0.5574**	0.4817**	0.4716**	0.0767	−1.4044**
β_{2c}	0.0411**	0.6179**	−0.0117	−0.1565	−0.0023	−0.0150	0.4924*	0.2577**	−0.0229**	0.1081**	−0.0023
β_{2h}	0.9241**	0.8886**	0.9430**	0.9094**	0.9236**	0.9449**	0.9488**	0.9548**	0.8997**	0.9273**	0.7049**
β_{2e11}	0.0526	0.1009**	0.0453	0.0449**	0.0734**	0.0420**	0.0359**	0.0217*	0.0807**	0.0565**	0.2304**
β_{2e12}	0.0243	−0.0230	0.0090	0.0410*	−0.0090	0.0121	0.0081	0.0212	0.0123	−0.0050	−0.0543**
$\beta_{2\mathrm{MON}}$	−0.0664*	−0.9980**	0.1528	0.2862	−0.2589**	−0.0928	−0.9959*	−0.3034**	0.1096*	−0.1065*	0.7442**

β_{2TUE}	−0.2654**	−0.9876**	−0.2901	−0.1284	0.2242**	−0.3290	−0.6991*	−0.6330**	0.2051**	−0.2034*	0.9228**
β_{2WED}	0.3245**	−0.0538	0.4857*	0.7341**	0.2726**	0.1144	0.1027	0.1238	−0.2402*	0.1350	2.3251**
β_{2THU}	0.0236	−0.5454**	−0.1392	0.2608	−0.0531*	0.5426*	−0.6882*	−0.2875**	0.2636**	−0.2069**	−0.2276**
d_0	0.4281**	0.4165**	1.0910**	0.8359**	0.4475**	1.1045**	0.7542**	1.2733**	0.6906**	0.7896**	0.6891**
d_1	−0.3949**	−0.6121**	−0.3320**	−0.3613**	−0.3168**	−0.2807**	−0.3617**	−0.2930**	−0.3763**	−0.2147**	−0.4629**
d_2	−0.0065	−0.0133	−0.0037	−0.0097	−0.0164*	−0.0091	−0.0043	−0.0160**	−0.0070*	−0.0192	−0.0100
c_1	−0.2757**	−0.3138**	−0.7658**	−0.6917**	−0.4180**	−0.3964**	−0.4618**	−0.7930**	−0.3713**	−0.5602**	−0.5823**
c_{12}	−0.5421**	−0.4499**	−0.8627**	−0.6773**	−0.5043**	−0.4143**	−0.9476**	−0.8758**	−0.5740**	−0.5703**	−0.7292**
c_2	−0.1179**	−0.1335**	−0.2451**	−0.1757**	−0.0819**	−0.1951**	−0.2331**	−0.2835**	−0.2107**	−0.1840**	−0.1521**
c_3	−0.0959**	−0.1047**	−0.2684**	−0.2280**	−0.1246**	−0.166**	−0.2018**	−0.2101**	−0.2424**	−0.1916**	−0.2125**
c_4	0.0077**	0.0122	−0.0115	−0.0016	0.0115	−0.0463*	0.0051	−0.0388*	−0.0079	−0.0106	0.0308**
c_5	−0.0586*	−0.1412**	−0.0112	−0.0047	0.0334	−0.1189	0.0051	−0.1387**	−0.0429	−0.0923*	0.1395*
c_{MON}	−0.0370	0.0215	−0.0548	−0.0645	−0.0604	−0.0999**	−0.017	0.0217	0.0471	−0.0321	−0.1769**
c_{TUE}	−0.0399	−0.1237*	−0.0129	−0.0243	−0.0921*	−0.1817**	−0.0181	0.0293	0.0496	−0.0584	−0.1731**
c_{WED}	−0.0684	−0.1582**	−0.0944**	−0.0893*	−0.1171**	−0.1892**	−0.1239**	−0.0822*	−0.0145	−0.0623	−0.0058
c_{THU}	−0.0395	−0.1322**	−0.0596*	0.0164	−0.1042**	−0.1774**	−0.0137	−0.0268	−0.0704	−0.0389	0.0390
Panel A											
Log − L	−8748	−9191	−6861	−7548	−8315	−9049	−7953	−7497	−6841	−5547	−10842
H0: $c_1 = c_{12}$	12.6334**	4.5802*	0.9560	0.0265	2.2503	0.1102	99.3826**	1.5328	6.7117**	0.0261	7.4893**
LB Q(20)[(1)]	37.8137**	41.6730**	34.4325*	30.5309	46.6524**	27.1261	36.4210*	44.1169**	22.7443	23.9088	24.1852
LB Q^2(20)[(2)]	21.2515	18.3222	15.3185	37.6293**	21.6487	26.6952	22.7405	28.7062	14.2955	35.3576*	16.5118

Note : *,** = significant at the 5 and 1 percent level, respectively.[(1), (2)]Ljung–Box test of white noise (of up to 20 lags) for the estimated standardized residuals from the model, $z_t = e_t/\sqrt{h_t}$ and squared $(z_t)^2$, respectively.

A number of other determinants of autocorrelation are also considered which have been found in the previous literature to be important. For our sample of individual stocks, above average changes in price have a significant negative impact on autocorrelation for 18 stocks. The exceptions are Diageo where only the above average positive return coefficient is negative and significant at 1% and Barclays where neither is significant. Traded volume has a negative and significant impact on autocorrelation for the FTSE index as well as for Glaxo Smith Cline, Aviva, Sainsbury and BOC. For nine stocks however, traded volume is found to have a positive and significant impact on autocorrelation while for the remaining seven stocks no relationship is found. Thus, the results provide clear evidence of a relationship between autocorrelation and traded volume however no clear consensus exists as to the nature of this relationship. In terms of the impact of the economic cycle, autocorrelation should be greater during a period of rising stock prices, and the index as well as 13 individual stocks exhibit a negative sign (of which 8 are significant) indicating that autocorrelation is lower during a recession which is as expected. The significant and positive coefficient for Barclays, Unilever and Imperial Chemicals however, are not consistent with expectations. Finally, evidence of a day-of-the-week effect can be found in the autocorrelation equation as roughly half of the estimates are negative and significant for the Tuesday, Wednesday and Thursday dummy variables. These results suggest that autocorrelation on these three days tends to be lower than autocorrelation evidence on Fridays which is the omitted case. When compared to the previous literature, these results are broadly consistent with those found for US stocks which trade under a very different platform.

5. Conclusion

The presence of serial correlation in security prices has important implications for market efficiency and trading strategies. Despite this importance, however, little is known about the determinants of autocorrelation. The purpose of this paper is to build on the nascent literature which has considered the determinants of autocorrelation. The method specified in this paper overcomes a number of problems which have impacted on the previous literature in terms of the dynamics driving the variation in the autocorrelation estimates, possible problems related to the endogeneity of the variables tested, and the efficiency of the estimation procedure. Consistent with the previous literature, this paper finds evidence of a relationship between autocorrelation and volatility, above average returns, traded volume, the business cycle and the day-of-the-week.

The main contribution of this paper is the identification of an asymmetry in the relationship between volatility and autocorrelation. Distinguishing between increases in volatility caused by a rise in prices and a fall in prices, the estimation results document a greater change in autocorrelation where the increase in volatility is caused by a rise in prices. This asymmetry is argued to be the result of short sales restrictions that limit the ability of investors to profit in a falling market. The difference between quote- and order-driven markets does not appear to impact on the known determinants of autocorrelation as our results are similar to those for the US. The implication of our study is that when modelling autocorrelation, the relationships may be more complex than has been previously documented. In this paper, we find that the nature of the relationship between autocorrelation and volatility has an asymmetry which is linked to short selling. This has important implications for policy with respect to trading rules which may impact on the market dynamics in unexpected ways. In the context of our work, controls on short selling appears to have an impact on the intertemporal characteristics of the market. Further work is needed in this area to attempt to uncover other determinants of autocorrelation paying special attention to the nature of the relationship as it is not obvious that simple linear determinism can be assumed.

Finally, the unconditional and average conditional autocorrelation estimate were compared and in comparison provide similar information. The former, however, does not indicate the presence of a number of stylised characteristics of autocorrelation including the presence of trends and structural breaks. Subperiod point estimates of autocorrelation verify the presence of these patterns and suggests unconditional autocorrelation estimates omit important information about the variability of autocorrelation which may be useful for analysis.

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