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VOLUME AND GARCH EFFECTS FOR DUAL-LISTED EQUITIES: EVIDENCE FROM IRISH EQUITIES

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ABSTRACT

This paper investigates the volume-volatility relationship for Irish shares, using daily trading volume for 14 of the largest traded Irish stocks, for the period 2 June 2000 through to 28 March 2003. Our results show that a strong contemporaneous volume-volatility correlation exists for Irish stocks. However, ARCH and GARCH effects remain statistically significant for nearly half of Irish stocks, although they are significantly reduced. We also find an asymmetric effect of volume trading on volatility. Trading on the UK stock market has a disproportional effect on volatility of Irish stocks compared to trading on the Irish market. This suggests a potential dual-listed volume-volatility puzzle.

INTRODUCTION

One of the recent growth areas in empirical research on stock prices has been in modelling price volatility. Researchers have offered a number of potential explanations of stock price volatility including macroeconomic volatility, corporate profitability, operating leverage and trading volume (Schwert, 1989). More recent studies have tended to concentrate on market microstructure explanations. These include the existence of autocorrelation in the news arrival process (Diebold and Nervole, 1989), agents' slow adaptation to news (Brock and LeBaron, 1996) and other volume trading market microstructure effects (Bollerslev and Domowitz, 1991; O'Hara, 1995).

The use of the generalised autoregressive conditional heteroskedasticity (GARCH) model is dominant in the price volatility literature as it readily allows for modelling jointly the time-varying nature of stock price volatility and the explanatory variables of this volatility. Within this framework the most tested hypothesis is the volume-volatility relationship. Lamoureux and Lastrapes' (1990) influential paper shows that, for a sample of 20 US stocks, autoregressive conditional heteroskedasticity (ARCH) effects become insignificant with the inclusion of volume in the conditional variance equation.

In general, a positive volume-volatility relationship exists for equities (Karpoff, 1987; Schwert, 1989; Jones, Kaul and Lipson, 1994). This is consistent with a number of suggested propositions, for example (i) if investors have heterogeneous beliefs, new information will cause both price changes and trading; (ii) if some investors use price movements as information on which to make trading decisions, large price changes will cause large trading volume (Schwert, 1989).

While a voluminous empirical literature on the daily return-volume relationship is available for developed and highly liquid stock markets in industrial countries, there is limited evidence from less developed and developing stock markets. This is the case for the Irish stock market.

We investigate the volume-volatility relationship for Irish shares, using daily trading volume (number of shares traded) for 14 of the largest traded Irish stocks (see **Table 1**), for the period 2 June 2000 through to 28 March 2003. These 14 stocks account for over 85 per cent of the total Irish stock market capitalisation.

The increased interest in the global aspects of financial markets motivates a further contribution of this paper. In particular, with an increasing number of stocks listing on more than one stock market, there is a need for greater understanding of the transmission of price behaviour between markets (Bae, Cha and Cheung, 1999). The Irish equities considered, having full listing on the Dublin Stock Exchange, are also listed on the London Stock Exchange. Gallagher and Twomey (1998) found that there are significant sectoral and market spillover effects from the UK on the price movement of Irish equities. In this paper we also test the source of the volume-volatility relationship for dual-listed Irish equities. Using disaggregated volume data, we investigate the relative importance of volume trading on both the London and Dublin stock markets in explaining conditional variance of returns. This approach also allows us to investigate the robustness of the volume-volatility relationship to the source of the volume trading.

The remainder of this paper is organised as follows. A description of the theoretical background and motivation for the analysis is followed by an outline of the econometric methods and theoretical explanation for the volume-volatility relationship. Two further sections presenting a summary of the data and reporting the empirical results precede the concluding remarks.

VOLUME-VOLATILITY RELATIONSHIP

Empirical evidence supports the general proposition of a positive relation between stock volatility (measured as absolute or squared price changes) and trading volume (for a comprehensive summary of the literature see Karpoff, 1987)[1]. This positive relationship was first documented in Ying (1966) who found that a small volume is usually accompanied by a fall in price, while a large increase in volume is accompanied by either a large rise in price or a large fall in price. More recent studies have shown a positive volume-volatility relationship in modelling individual securities and portfolios (Jones et al., 1994). However, for a number of these studies the statistical significance of this positive relationship is weak (Karpoff, 1987)[2].

Schwert (1989) outlines three propositions that are consistent with a positive relation between volatility and volume. First, if investors have heterogeneous beliefs, new information will cause both price changes and trading activity (Harris and Raviv, 1993; Shalen, 1993). Second, if some investors use price movements as information on which to make trading decisions, large price movements will cause large trading volume. Third, if there is short term price pressure due to illiquidity in secondary trading markets, large trading volume that comprises predominantly either buy or sell orders will cause price movements.

Furthermore, Jones et al. (1994) find that in competitive models with asymmetric information, volume is positively related to the quality (or precision) of information possessed by informed traders. In strategic models, asymmetric information also leads to trading, but a monopolist informed trader could camouflage his trading activity through numerous small-sized trades rather than one large trade as in the former model. The volume of the informed agents is positively related to the quality of their information; therefore, a positive relation between volume and absolute price changes exists.

Schwert's (1989) main argument is that volume induces price changes because price changes are an important input into trading strategies. A belief in price persistence will result in many investors wishing to trade in the same direction when there is a price movement. This herd mentality becomes a self-fulfilling prophecy as the increased trading exacerbates the change in price, which in turn influences more investors to trade in the same direction. In contrast, Jones et al. (1994) argue that volume is related to volatility because it reflects the extent of disagreement about asset value based on either differential information or differences in opinion.

The mixture of distribution hypothesis (MDH) put forward by Clarke (1973), Epps and Epps (1976), Tauchen and Pitts (1983) and, more recently, by Lamoureux and Lastrapes (1990) has also been offered as an explanation linking price change, volume and the rate of information flow. According to the MDH a serially correlated mixing variable measuring the rate at which information arrives to the market explains the time-varying volatility in stock prices.

From the market microstructure perspective, price movements are caused primarily by the arrival of new information and the process that incorporates this information into market prices. Andersen (1996) suggests that variables such as the trading volume, the number of transactions, the bid-ask spread or market liquidity are related to the price volatility process.

A number of considerations are relevant when selecting a dynamic representation for the information variable. First, casual empiricism suggests that news arrivals are positively correlated. When unanticipated news breaks on a given day, more detailed disclosures tend to follow over the next few days or weeks, and different interpretations of the circumstances leading to the event surface. This leads to keeping the story in the headlines for an extended period of time. Second and more importantly, due to the success of modelling return volatility dynamics by means of GARCH processes, it is clear that an information arrival process governing the dynamic features of price volatility must display a similar type of positive conditional dependency (Andersen, 1996).

Empirical researchers have documented persistence in abnormal trading volume after an informational event and after prices have adjusted (Beaver, 1968; Morse, 1980). One reason for this is that some investors are late in the information queue. These investors adjust their holdings, ignorant of the fact that their information is old. Also, the information creates the desire to trade among some investors whose demands are not immediately cleared, perhaps because they face costs of coming to the market (Karpoff, 1986).

Furthermore, O'Hara (1995) notes that price and volume are perhaps the most obvious market statistics to provide information to uninformed market participants. Volume provides traders with the ability to sort out the effects of the quality of information from the direction of information events impounded in price. In this way, it acts as a signal of quality in a way independent from price because volume is not normally distributed. Price changes are interpreted as the market's evaluation of new information, while the corresponding volume is considered an indication of the extent to which investors disagree about the meaning of the information (Beaver, 1968).

Karpoff (1987) suggests that it is likely that observations of simultaneous large trading volumes and large price changes (either positive or negative) can be traced to their common ties to information flows (for example, as in the sequential information model)[3], or their common ties to a directing process that can be interpreted as the flow of information (as in the MDH).

Empirical investigation of the role of trading volume in the GARCH equation of stock returns has been well documented for the US stock market (Lamoureux and Lastrapes, 1990; Kim and Kon, 1994; Andersen, 1996; Gallo and Pacini, 2000) and the UK stock market (Omran and McKenzie, 2000). In general, the bulk of empirical studies support the hypothesis that the inclusion of trading volume in a GARCH equation for returns reduces or eliminates the estimated persistence in the equation. These studies and others (Cornell, 1981; Schwert, 1989) have reported a strong positive contemporaneous correlation between daily trading volume and return volatility.[4]

ECONOMETRIC METHODS

Asset markets are characterised by periods of turbulence and tranquillity, that is to say large (small) forecast errors (of whatever sign) tend to be followed by further large (small) errors. Therefore there is persistence or clustering in the variance of the forecast errors (Cuthbertson, 1996, p. 438). Engle's (1982) ARCH representation has been shown to provide a good fit for many financial return time series (Bollerslev, 1987; Lamoureux and Lastrapes, 1988).

The MDH provides a theoretical explanation for the presence of ARCH and can be used to motivate the empirical tests of the effects of volume on the conditional volatility. Let r_t be the daily rate of return and β_0 the expected (average) daily rate of return. Therefore, the demeaned daily rate of return is given by:

(1) $\varepsilon_t = r_t - \beta_0$

Let δ_{jt} denote the jth intra-day equilibrium (demeaned) return increment in day t, which implies:

(2) $\varepsilon_t = \sum_{j=1}^{n_t} \delta_{jt}$

According to this model, the demeaned return over the full trading day ε_t, is the sum of the intra-day equilibrium returns δ_j, with $j = 1, 2, \ldots, n_t$ and where n_t is a random or mixing variable which represents the number of information arrivals to the market on day t that changes the equilibrium price. ε_t is drawn from a mixture of distributions, where the variance of each distribution depends upon the information arrival time. Equation (2) implies that daily returns are generated by a subordinate stochastic process, in which ε_t is subordinate to δ_{jt} and n_t is the directing process.

If δ_{jt} is iid with zero mean and constant variance (σ^2), and n_t is sufficiently large, then $\varepsilon_t | n_t \sim N(0, \sigma^2 n_t)$. GARCH may be explained as a manifestation of time dependence in the rate of evolution of intra-day equilibrium (demeaned) returns. To make the argument precise, we follow Lamoureux and Lastrapes (1990) in assuming that the daily number of information arrivals is serially correlated, given by:

(3) $n_t = k + b(L)n_{t-1} + u_t$

where k is a constant, b(L) is a lag polynomial of order q, and the residual u_t is white noise. Innovations to the mixing variable (n_t) (i.e. changes in the random rate at which information flows into the market) persist according to the autoregressive structure of b(L). Finally, define $\Phi_t = E(\varepsilon^2_t | n_t)$. Thus, if the mixture model is valid, $\Phi_t = \sigma^2 n_t$, and we can re-write (2) as:

(4) $\Phi_t = \sigma^2 k + b(L)\,\Phi_{t-1} + \sigma^2 u_t$

This equation captures the type of persistence in conditional variance that can be picked up by estimating a GARCH model. In particular, innovations to the information process lead to momentum in the squared residuals of daily returns. Because n_t is generally not observed, we employ daily trading volume as a proxy. In our analysis we assume that our volume variable is weakly exogenous[5] in the sense of Engle, Hendry and Richard (1983).

In the context of our study, the following GARCH (1,1) model is employed:

(5) $\varepsilon_{i,t} = r_{i,t} - \beta_0$

(6) $\varepsilon_{i,t} \mid \Omega_{t-1} \sim N(0,h_{i,t})$

(7) $h_{i,t} = \alpha_0 + \alpha_1\varepsilon^2_{i,t-1} + \alpha_2 h_{i,t-1} + \alpha_3 V_{i,t}$

where, for asset i, $r_{i,t}$ is the rate of return on the asset defined as $\ln(P_{i,t} / P_{i,t-1})$, where P is the price of asset i, β_0 is the average rate of return on the asset, the *residual is given by* $\varepsilon_{i,t}$ *which, given* the information set Ω_{t-1}, is normally distributed with zero mean and time-varying conditional variance $h_{i,t}$. $\varepsilon^2_{i,t-1}$ is news about volatility from the previous period, and $V_{i,t}$ is the daily trading volume of asset i. The sum $(\alpha_1 + \alpha_2)$ denote the degree of persistence in the conditional variance given a shock to the system. The parameters α_0, α_1, α_2, are constant such that α_0 is positive, $0 < \alpha_1, \alpha_2 < 1$, and $0 < (\alpha_1 + \alpha_2) < 1$.[6]

Due to the unique relationship between the Dublin and London Stock Exchanges, all listed Irish stocks considered are jointly and simultaneously traded in both markets. Using disaggregated volume data we can also look at the relative importance on volatility of trading in Irish equities on the Dublin and London markets. To test this hypothesis we define total trading volume as $V_{i,t}$, which is the sum of trading on the Dublin market ($V^D_{i,t}$) and trading on the London market as ($V^L_{i,t}$). The variance equation in the GARCH(1,1) can now be described as:

$$(8) \qquad h_{i,t} = \alpha_0 + \alpha_1\varepsilon^2_{i,t-1} + \alpha_2 h_{i,t-1} + \alpha_3 V^D_{i,t} + \alpha_4 V^L_{i,t}$$

Furthermore, to investigate the robustness of the volume-volatility relationship for Irish equities we also estimate the GARCH(1,1) model, given by equations (5)-(7), one further time where $V_{i,t}$ is defined as $V^D_{i,t}$.

The parameters of the GARCH system are estimated by computing the conditional log-likelihood function L, with

$$(9) \qquad L = -0.5\log h_t - 0.5\sum_{t-1}^{T} \varepsilon^2_t / h_t$$

Numerical maximisation of the log-likelihood function following the Berndt, Hall, Hall and Hausman (1974) algorithm yields the maximum likelihood estimates and associated asymptotic standard errors.

DATA AND PRELIMINARY ANALYSIS

Daily closing price and volume data for 14 Irish stocks for the 2 June 2000 to 28 March 2003 period were obtained from Datastream and the Irish Stock Exchange. The starting date was chosen to coincide with the change from a settlement based to a trading based methodology by the Irish Stock Exchange for calculating turnover and volume. For this reason volume data was not available from the Irish Stock Exchange before 2 June 2000. Descriptive statistics for trading volume on the Irish (Dublin) and UK (London) Stock Exchanges are presented in **Table 1**.[7]

TABLE 1: SUMMARY STATISTICS

Company	Mean daily return, %	Skewness	Kurtosis	ARCH(1)	Market capitalisation, % of overall Irish stock market	Average daily trading volume (in millions) on the Irish market	Average daily trading volume (in millions) on the UK market
Allied Irish Banks (AIB)	0.026	–0.900†	9.862†	60.926†	21.89	2.766 (66%)	1.396 (34%)
Anglo Irish Bank Corporation (ANG)	0.143	–0.182*	3.826†	183.195†	4.19	2.251 (66%)	1.148 (34%)
Bank of Ireland (BOI)	0.051	–0.175‡	1.404†	193.547†	18.68	4.027 (65%)	2.136 (35%)
CRH (CRH)	–0.052	–0.564†	7.165†	70.654†	13.54	1.690 (60%)	1.114 (40%)
Fyffes (FYF)	–0.026	0.044	4.043†	108.525†	0.82	1.496 (90%)	0.171 (10%)
Galen Holdings (GAL)	–0.050	–0.043	4.250†	124.844†	2.15	0.127 (20%)	0.503 (80%)
Greencore Group (GRE)	–0.014	–0.041	1.787†	162.128†	0.90	0.589 (92%)	0.050 (8%)
IAWS Group (IAWS)	0.021	0.742†	7.487†	84.138†	1.72	0.208 (96%)	0.008 (4%)
Independent News & Media (IND)	–0.152	–0.184*	4.130†	113.676†	1.35	1.350 (89%)	0.167 (11%)
Irish Life and Permanent (ILP)	0.019	–0.051	2.730†	133.900†	5.03	1.468 (92%)	0.126 (8%)
Kerry Group (KYG)	–0.015	–0.538†	6.241†	125.822†	4.37	0.303 (67%)	0.153 (33%)
Ryanair Holdings (RYN)	0.055	0.213*	4.557†	103.808†	9.33	1.976 (62%)	1.235 (38%)
United Drug (UTD)	0.070	0.247†	3.686†	148.801†	0.72	0.060 (93%)	0.005 (7%)
Waterford Wedgwood (WWD)	–0.206	–0.006	7.687†	149.164†	0.36	2.582 (91%)	0.252 (9%)

*Notes: The symbols †, * and ‡ indicate statistical significance at the one, five, and ten per cent levels, respectively. Figures in parentheses are the share of total volume trading on a particular stock in the respective market. The ARCH(1) is Engle's (1982) test for ARCH effects based on a Lagrange Multiplier test, and is a $\chi 2(1)$ statistic.*

For the stocks under study, on average, 75 per cent of trading volume is at the Dublin Stock Exchange. The main outlier is Galen Holdings, a Northern Ireland based company, where 80 per cent of trading is at the London Stock Exchange.

Returns are given by the first difference of the natural logarithms of stock prices. Preliminary unit root testing confirms that all the log price series are I (1) processes. We also tested for unit roots in the squared return series and volume data series. All series were found to be stationary, with a strong rejection of the unit root hypothesis at the one per cent level of significance. The results for the unit root testing are not reported here but are available on request from the authors. **Table 1** suggests that the sample moments for the unconditional return distributions indicate empirical distributions with heavy tails relative to the normal distribution. The majority of the series exhibit non-normality and are strongly leptokurtic. This finding is consistent with previous studies on the Irish stock market (Cotter, 1998; Gallagher and Twomey, 1998). Furthermore, the *Lagrange Multiplier* test (Engle, 1982) of ARCH (1) effects indicates non-linear dependencies in the return distribution in all 14 Irish stock returns.

EMPIRICAL RESULTS

In order to identify the conditional variance of returns in Irish shares, we first model the demeaned (using daily dummies) return series as a GARCH (1,1).[8] The GARCH model is estimated by maximum likelihood. **Table 2** reports the estimated results from the conditional variance equations for the Irish stocks and indicates that daily stock returns are characterised by the GARCH (1,1) model. The estimated coefficients α_1 (a measure of impact of news) and α_2 (α_1 and α_2 together measure persistence) are highly significant and consistent with other international studies (Lamoureux and Lastrapes, 1990; Kim and Kon, 1994; Gallo and Pacini, 2000; Omran and McKenzie, 2000). Moreover, all stocks indicate a high degree of persistence in volatility.

To investigate the volume-volatility relationship for Irish equities, we incorporate the alternative volume measures in the conditional variance equation in the GARCH (1,1) - as given in equations (5)-(7). **Table 3** reports the estimated results for the 14 Irish stocks. A strong contemporaneous correlation between trading volume (the number of shares traded, in millions) and return volatility exists.

TABLE 2: MAXIMUM LIKELIHOOD ESTIMATES OF GARCH (1,1) MODEL

$h_{i,t} = \alpha_0 + \alpha_1 \varepsilon^2_{i,t-1} + \alpha_2 h_{i,t-1}$, **where** $\varepsilon_{i,t} = r_{i,t} - \sum_{j=1}^{5} \beta_j$

Stock	α_1	α_2	$\alpha_1+\alpha_2$
AIB	0.134 (4.186)†	0.610 (6.953)†	0.744
ANG	0.324 (7.913)†	0.401 (6.124)†	0.725
BOI	0.114 (4.890)†	0.840 (28.956)†	0.954
CRH	0.037 (4.175)†	0.926 (68.886)†	0.963
FYF	0.218 (6.317)†	0.662 (18.778)†	0.880
GAL	0.125 (5.780)†	0.751 (23.904)†	0.876
GRE	0.111 (5.773)†	0.860 (42.894)†	0.971
IAWS	0.157 (6.628)†	0.763 (26.733)†	0.920
IND	0.263 (6.429)†	0.084 (1.494)	0.347
ILP	0.090 (4.393)†	0.847 (32.946)†	0.937
KYG	0.217 (8.106)†	0.703 (25.372)†	0.920
RYN	0.119 (7.915)†	0.837 (48.850)†	0.956
UTD	0.329 (7.142)†	0.478 (10.530)†	0.807
WWD	0.130 (8.538)†	0.851 (56.482)†	0.981

*Notes: See **Table 1** for definition of stocks. In the mean equation ε_{it}, β_j are daily dummies. Maximum likelihood estimation of the GARCH (1,1) model using the Berndt et al. (1974) algorithm. t-statistics are in parentheses. The symbols †, *, and ‡ indicate statistical significance at the one, five and ten per cent levels, respectively.*

TABLE 3: VOLUME AND GARCH EFFECTS

$$h_{i,t} = \alpha_0 + \alpha_1\varepsilon^2_{i,t-1} + \alpha_2 h_{i,t-1} + \alpha_3 V_{i,t}\ , \text{ where } \varepsilon_{i,t} = r_{i,t} - \sum_{j=1}^{5}\beta_j$$

Stock	α_1	α_2	α_3	$\alpha_1+\alpha_2$
AIB	0.107 (3.439)†	0.022 (0.261)	0.539 (7.748)†	0.129
ANG	0.341 (6.565)†	0.105 (3.686)†	0.827 (11.033)†	0.446
BOI	0.169 (3.953)†	0.289 (3.876)†	0.366 (6.667)†	0.458
CRH	0.082 (6.036)†	–	1.321 (24.643)†	0.082
FYF	0.224 (5.068)†	–	2.280 (10.751)†	0.224
GAL	0.167 (4.782)†	0.015 (0.363)	7.040 (9.377)†	0.182
GRE	0.255 (4.841)†	0.220 (3.591)†	1.807 (6.047)†	0.475
IAWS	0.157 (6.575)†	0.763 (26.187)†	–	0.920
IND	0.253 (6.851)†	0.050 (0.988)	0.725 (3.690)†	0.303
ILP	0.164 (9.254)†	–	2.133 (26.928)†	0.164
KYG	0.249 (6.182)†	0.075 (1.646)‡	1.145 (7.932)†	0.324
RYN	0.053 (2.058)	–	1.762 (10.876)†	0.053
UTD	0.336 (6.579)†	0.459 (10.064)†	1.097 (2.121)*	0.795
WWD	0.212 (7.642)†	0.658 (17.337)†	0.504 (6.416)†	0.870

*Notes: See **Table 1** for a definition of stocks. In the mean equation εit , βj are daily dummies. Maximum likelihood estimation of the GARCH (1,1) model using the Berndt et al. (1974) algorithm. t-statistics are in parentheses. The symbols †, *, and ‡ indicate statistical significance at the one, five and ten per cent levels, respectively. Zero values for parameters due to non-negativity constraints of the conditional variance are not reported. Daily trading volume Vi,t is expressed as millions of shares traded.*

With the inclusion of volume in the conditional variance equation, volatility persistence (GARCH effects) and ARCH effects are significantly reduced. In fact, in half of the cases the GARCH term is not significantly different from zero at the five per cent level. There exists a strong positive and significant (at the five per cent level of significance) volume-volatility relationship (given by α_3) for the sample of Irish stocks. Similar results are reported for the majority of tests carried out on the US and UK stock markets (Lamoureux and Lastrapes, 1990; Jones et al., 1994; Kim and Kon, 1994; Gallo and Pacini, 2000; Omran and McKenzie, 2000) on the Korean market (Pyun, Lee and Nam, 2000) and on the Australian market (Brailsford, 1996).

ARCH and GARCH effects remain statistically significant for a number of stocks, in particular, ANG, BOI, GRE, IAWS, KYG, UTD and WWD (see **Table 1** for company names). This indicates that additional information about the variance of the stock return process exists after accounting for trading volume, and is consistent with the proposition that volume provides information on the precision and dispersion of information signals, rather than serving as a proxy for the information signal itself (Blume, Easley and O'Hara, 1994). In comparing developed with less developed stock markets, international studies indicate that ARCH and GARCH effects disappear when volume is incorporated into the conditional variance equation for developed stock markets, with less conclusive results for stock markets that are less developed (Lamoureux and Lastrapes, 1990; Gallo and Pacini, 2000; Bohl and Henke, 2001; Huang and Yang, 2001).

There are a number of possible explanations for this result. First, the Irish stock market (like other less developed markets) is small, relatively illiquid, and with many stocks thinly traded. Similar results were found for the Polish stock market (Bohl and Henke, 2001) and the Taiwan market (Huang and Yang, 2001). In terms of our sample, stocks that show no significant reduction in the ARCH and GARCH effects also have over twice as many days with no price change, on average. The top three most thinly traded stocks, by days of inactivity in share price movement (on average 28 per cent of days exhibit no price movement), are IAWS, UTD and WWD. These are also the stocks that show the least reduction in ARCH and GARCH effects.

Second, the dual listed nature of Irish stocks potentially introduces an asymmetric volume effect on volatility depending on the source of trading. We explore this latter explanation by decomposing the volume data into the location source of the trades that take place.

Source of volume-volatility relationship

We estimate equation (8) using the disaggregated volume data and report the results in **Table 4**. The results show that the strong contemporaneous volume-volatility relationship reported I n **Table 3** is robust to the definition of volume used. Moreover, similar effects of disaggregated trading volume on volatility persistence and ARCH effects are reported. Thus the dual listed nature of Irish stocks does not explain the presence of statistically significant ARCH and GARCH effects.

TABLE 4: VOLUME AND GARCH EFFECTS: BASED ON DISAGGREGATED TRADING DATA

$$h_{i,t} = \alpha_0 + \alpha_1\varepsilon^2_{i,t-1} + \alpha_2 h_{i,t-1} + \alpha_3 V^D_{i,t} + \alpha_4 V^L_{i,t}\text{ , where } \varepsilon_{i,t} = r_{i,t} - \sum_{j=1}^{5}\beta_j$$

Stock	α_1	α_2	α_3	α_4	$\alpha_1+\alpha_2$	Relative impact of trading on Irish market, %	Relative impact of trading on UK market, %
AIB	0.109 (3.520)†	0.017 (0.221)	0.367 (3.074)†	1.036 (3.725)†	0.126	41.2	58.8
ANG	0.332 (6.486)†	0.104 (3.563)†	1.224 (2.259)‡	–	0.436	100.0	0.0
BOI	0.124 (3.976)†	0.739 (12.503)†	0.142 (3.618)†	–	0.863	100.0	0.0
CRH	0.066 (5.000)†	–	1.028 (5.646)†	1.921 (8.959)†	0.066	44.8	55.2
FYF	0.189 (4.517)†	–	1.839 (8.480)†	14.687 (6.220)*	0.189	52.3	47.7
GAL	0.173 (5.140)†	0.009 (0.240)	21.705 (6.009)†	3.787 (4.599)†	0.182	59.2	40.8
GRE	0.246 (4.744)†	0.225 (3.949)†	1.557 (5.275)†	11.534 (3.871)†	0.471	61.6	38.4
IAWS	0.157 (6.500)†	0.763 (25.861)†	–	–	0.920	–	–
IND	0.251 (6.803)†	0.055 (1.088)	0.830 (3.358)†	–	0.306	100.0	0.0
ILP	0.171 (7.867)†	–	1.500 (12.507)†	8.354 (6.509)†	0.171	67.6	32.4
KYG	0.246 (8.237)†	0.614 (18.790)†	0.478 (0.417)	–	0.860	100.0	0.0
RYN	0.047 (1.651)‡	–	–	4.841 (5.922)†	0.047	0.0	100.0
UTD	0.334 (6.460)†	0.461 (9.600)†	1.337 (2.280)*	–	0.795	100.0	0.0
WWD	0.199 (7.164)†	0.680 (18.692)†	0.301 (3.544)†	2.423 (4.482)†	0.879	56.0	44.0

*Notes: See **Table 1** for a definition of stocks. In the mean equation ε_{it}, β_j are daily dummies. Maximum likelihood estimation of the GARCH (1,1) model using the Berndt et al. (1974) algorithm. t-statistics are in parentheses. The symbols †, *, and ‡ indicate statistical significance at the one, five and ten per cent levels, respectively. Zero values for parameters due to non-negativity constraints of the conditional variance are not reported. Daily trading volume $V^D_{i,t}$ and $V^L_{i,t}$ are expressed in millions of shares traded.*

Table 4 also reports the impact of trading on the Dublin and London markets on the time-varying volatility that is explained by volume. The impact which trading on the Dublin market has on the price volatility that is explained by volume is calculated as follows:

$$\alpha_3 V^*_D \,/\, (\alpha_3 V^*_D + \alpha_4 V^*_L) \tag{10}$$

where α_3 and α_4 are the coefficient values estimated when disaggregated trading volume is included in the conditional variance equation, V^*_D is the average daily trading volume (in millions) on the Irish market, and V^*_L is the average daily trading volume (in millions) on the UK market. Taking AIB as an example, the calculations reported in **Table 4** show that 41 per cent of the price volatility of AIB that is explained by trading volume arises from trading on the Dublin market, with the remainder attributed to the London market.

The relative impact reported indicates that the market where trading occurs does not have a significantly different effect on volatility (that is explained by trading volume). However, the absolute impact (represented by α_3 and α_4), indicates that the UK market has a larger impact on volatility, even though 75 per cent of trading occurs on the Irish market. This introduces a potential new volume-volatility puzzle, since one would not expect that the market on which shares are traded would have significantly differing impacts on volatility. Given the potential high correlation between the Dublin and London volume series, a cautious interpretation is required. In our sample this, in particular, applied to three stocks, ANG, KYG, and RYN, all of which have a correlation coefficient between the two volume series that is greater than 0.9.

Institutional factors, tax burdens or transaction costs, along with investors' idiosyncratic investment rules, offer possible explanations for the dual listed volume-volatility puzzle (French and Poterba, 1991). Podpiera (2001), using an error correction approach, reports a similar dual-listing puzzle and suggests this supports a partial fragmentation of stock markets. A related explanation is the "insider-outsider issue", which suggests that there may be greater information content from a trader outside the home market. However, further study is necessary to explain this dual-listed volume-volatility puzzle that arises for the Irish stocks. As a result of globalisation, many stocks are traded on different markets. Hence, the dual-listed volume-volatility puzzle is relevant to many international stocks, with emphasis on those traded on the more illiquid markets.

Robustness of findings

The majority of trading in individual Irish shares is on the Dublin Stock Exchange. Since we are modelling movements in stock prices on the Irish market, **Table 5** reports the analyses of the volume-volatility relationship, with volume measured as the number of shares traded (in millions) on the Dublin Stock Exchange. Apart from providing an additional test of the robustness of the earlier volume-volatility results as reported in **Table 3**, the results provide a comparison with international studies, which have concentrated on volume trading in a single stock market

(Gallo and Pacini, 2000). The results are very similar to those reported for overall volume trading; the volume-volatility relationship appears to be robust to the definition of volume and the results from international studies.

TABLE 5: VOLUME AND GARCH EFFECTS: BASED ON TRADING ON THE DUBLIN MARKET

$$h_{i,t} = \alpha_0 + \alpha_1\varepsilon^2_{i,t-1} + \alpha_2 h_{i,t-1} + \alpha_3 V^D_{i,t}\text{ , where } \varepsilon_{i,t} = r_{i,t} - \sum_{j=1}^{5}\beta_j$$

Stock	α_1	α_2	α_3	$\alpha_1+\alpha_2$
AIB	0.116 (3.330)†	0.076 (0.843)	0.630 (7.658)*	0.192
ANG	0.332 (6.500)†	0.104 (3.579)†	1.224 (10.929)†	0.436
BOI	0.124 (4.114)†	0.739 (12.795)†	0.142 (3.815)†	0.863
CRH	0.056 (2.248)*	0.020 (0.258)	1.653 (9.924)†	0.076
FYF	0.243 (5.574)†	–	2.255 (9.824)†	0.243
GAL	0.179 (5.200)†	0.077 (2.233)*	29.631 (7.780)†	0.256
GRE	0.256 (4.871)†	0.235 (3.706)†	1.730 (5.849)†	0.491
IAWS	0.157 (6.569)†	0.763 (26.151)†	–	0.920
IND	0.251 (6.845)†	0.055 (1.088)	0.830 (3.709)†	0.306
ILP	0.114 (3.138)†	0.223 (4.215)†	1.337 (9.344)†	0.337
KYG	0.246 (8.240)†	0.614 (18.799)†	0.478 (5.663)†	0.860
RYN	0.070 (2.794)†	–	2.615 (9.251)†	0.070
UTD	0.334 (6.524)†	0.461 (10.204)†	1.348 (2.427)*	0.795
WWD	0.209 (7.886)†	0.668 (18.068)†	0.501 (6.067)†	0.877

Notes: See ***Table 1*** *for a definition of stocks. In the mean equation ε_{it} , β_j are daily dummies. Maximum likelihood estimation of the GARCH (1,1) model using the Berndt et al. (1974) algorithm. t-statistics are in parentheses. The symbols †, *, and ‡ indicate statistical significance at the one, five and ten per cent levels, respectively. Zero values for parameters due to non-negativity constraints of the conditional variance are not reported. Daily trading volume $V^D_{i,t}$ is expressed as millions of shares traded.*

A number of researchers have found evidence of asymmetry in stock price behaviour - negative surprises seem to increase volatility more than positive surprises (see Bollerslev, Chou and Kroner, 1992, and Poon and Granger, 2002, for a review of this evidence). Evidence of this stylised fact is often described as the leverage effect. Given that the preliminary data analysis found evidence of non-normality in the return series and given the international evidence of asymmetry in the surprise or news variable ($\varepsilon^2_{i,t-1}$), we estimate Nelson's (1991) exponential GARCH (EGARCH) model. The EGARCH models are estimated using maximum likelihood under the assumption that $\varepsilon_{i,t}$ follows a generalised error distribution (Nelson, 1991). **Table 6** reports the estimated parameter values of the individual EGARCH (1,1) equations. The EGARCH (1,1) results show that there is little asymmetry in the surprise/news variable. For this reason the results are remarkably robust to the specification of the conditional variance equation.

TABLE 6: VOLUME AND EGARCH EFFECTS

The three EGARCH (1,1) representations are:

(i) $\log(h_{i,t}) = \alpha_0 + \alpha_1 \left|\frac{\varepsilon_{i,t-1}}{\sqrt{h_{i,t-1}}}\right| + \gamma_1 \frac{\varepsilon_{i,t-1}}{\sqrt{h_{i,t-1}}} + \alpha_2 \log(h_{it-1})$

(ii) $\log(h_{i,t}) = \alpha_0 + \alpha_1 \left|\frac{\varepsilon_{i,t-1}}{\sqrt{h_{i,t-1}}}\right| + \gamma_1 \frac{\varepsilon_{i,t-1}}{\sqrt{h_{i,t-1}}} + \alpha_2 \log(h_{it-1}) + \alpha_3 V_{i,t}$; and

(iii) $\log(h_{i,t}) = \alpha_0 + \alpha_1 \left|\frac{\varepsilon_{i,t-1}}{\sqrt{h_{i,t-1}}}\right| + \gamma_1 \frac{\varepsilon_{i,t-1}}{\sqrt{h_{i,t-1}}} + \alpha_2 \log(h_{it-1}) + \alpha_4 VD_{i,t} + \alpha_5 VL_{i,t}$,

where for (i)–(iii), $\varepsilon_{i,t} = r_{i,t} - \Sigma_{j=1}^{5}\beta_j$

Stock		α_1	γ_1	α_2	α_3	α_4	α_5
AIB	(i)	0.223†	–0.050	0.884†			
	(ii)	0.342†	–0.042	0.414†	0.075†		
	(iii)	0.340†	–0.042‡	0.415†		0.082†	0.058
ANG	(i)	0.461†	–0.059	0.673†			
	(ii)	0.495†	–0.088	0.242*	0.119†		
	(iii)	0.423†	–0.082	0.094		0.146	0.078
BOI	(i)	0.196†	–0.086†	0.954†			
	(ii)	0.225†	–0.093†	0.906†	0.011†		
	(iii)	0.206†	–0.080†	0.906†		0.025†	–0.019
CRH	(i)	0.172†	–0.038	0.935†			
	(ii)	0.241†	–0.003	0.118	0.254†		
	(iii)	0.245†	–0.002	0.140		0.173†	0.402†
FYF	(i)	0.391†	–0.003	0.589†			
	(ii)	0.409†	–0.055	0.262*	0.175†		
	(iii)	0.388†	–0.058	0.241‡		0.153†	0.834†
GAL	(i)	0.383†	–0.224†	0.787†			
	(ii)	0.430†	–0.264†	0.700†	0.300†		
	(iii)	0.294†	–0.196†	0.315†		1.600†	0.196†

Stock		α_1	γ_1	α_2	α_3	α_4	α_5
GRE	(i)	0.365†	–0.015	0.903†			
	(ii)	0.425†	0.000	0.861†	0.119†		
	(iii)	0.390†	–0.036	0.873†		0.081‡	0.339
IAWS	(i)	0.362†	–0.088	0.910†			
	(ii)	0.311†	–0.070	0.902†	–0.035		
	(iii)	0.330†	–0.090‡	0.832†		0.015	–1.641
IND	(i)	0.313†	–0.091	0.628†			
	(ii)	0.346†	–0.092	0.418†	0.091†		
	(iii)	0.293†	–0.060	0.468†		0.102†	–0.061
ILP	(i)	0.214†	–0.060‡	0.941†			
	(ii)	0.274†	0.037	0.052	0.330†		
	(iii)	0.305†	0.020	0.149		0.234†	1.924†
KYG	(i)	0.356†	–0.004	0.915†			
	(ii)	0.454†	–0.040	0.856†	0.193*		
	(iii)	0.461†	–0.039	0.846†		–1.118	2.852
RYN	(i)	0.155†	–0.095†	0.965†			
	(ii)	0.238‡	–0.098	0.039	0.157†		
	(iii)	0.227*	–0.106	0.325*		0.024	0.297‡
UTD	(i)	0.158‡	–0.042	0.737†			
	(ii)	0.202†	–0.053	0.758†	0.118		
	(iii)	0.213†	–0.051	0.666†		0.061	0.198
WWD	(i)	0.148†	–0.120†	0.975†			
	(ii)	0.192†	–0.154†	0.926†	–0.028†		
	(iii)	0.173†	–0.160†	0.925†		0.018‡	0.203*

*Notes: See **Table 1** for a definition of stocks and **Table 3** and **4** for definitions of variables. Maximum likelihood estimation of the EGARCH (1,1) model using the Berndt et al. (1974) algorithm. The symbols †, *, and ‡ indicate statistical significance at the one, five and ten per cent levels, respectively.*

CONCLUSION

This study examines the correlation between daily trading volume and time varying volatility for 14 Irish stocks, from 2 June 2000 to 28 March 2003. These stocks are dually listed on the Dublin and London stock markets. The effects of trading volume on the GARCH model are also outlined. The Irish stocks under study possess a high degree of volatility persistence as shown in the GARCH (1,1) model, supporting the hypothesis that ARCH reflects an uneven but persistent flow of information to stock markets.

With the inclusion of trading volume (in millions of shares traded) in the conditional variance equation, we find a strong contemporaneous volume-volatility correlation for Irish stocks. Consistent with previous studies (Lamoureux and Lastrapes, 1990; Kim and Kon, 1994; Gallo and Pacini, 2000; Omran and McKenzie, 2000), volatility persistence and ARCH effects are significantly reduced with the inclusion of trading volume in the variance equation. However, ARCH and GARCH effects remain statistically significant for nearly half of Irish stocks, unlike the results from the more developed markets. The results are robust to the specification of the conditional variance equation and definition of volume. We attribute this finding to the low level of market liquidity (and associated thin trading) and not to the dual-listed nature of Irish stocks.

In assessing the impact of the source of trading, we find an asymmetric effect of volume trading on volatility. Trading on the UK stock market has a disproportional effect on volatility of Irish stocks compared to trading on the Irish market. This suggests a dual-listed volume-volatility puzzle, since the market on which trading activity occurs matters in terms of its impact on volatility. Further study is necessary to fully investigate this potential puzzle, where emphasis should be given to institutional factors, market fragmentation, investors' idiosyncratic investment rules and the thinly traded nature of Irish stocks.

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NOTES

1 A number of empirical papers provide indirect evidence on the relationship between trading volume and stock returns. It is well documented that returns on the New York Stock Exchange (NYSE) tend to follow a U-shaped pattern during the trading day (Harris, 1989). *Intraday volatility also follows a U-shaped pattern. Similar results have* been reported for the Hong Kong Stock Exchange (Ho and Cheung, 1991) and the London Stock Exchange (Yadav and Pope, 1992). Wei (1992) shows that trading volume follows a U-shaped pattern during the trading day. Hence, considering the similar patterns observed for volume and variance, a positive correlation between the variance and trading volume may be inferred.

2 A further strand of this literature considers the nature of the price-volume relationship for event studies (Beaver, 1968; Jain, 1988).

3 Copeland (1976) derives a model in which common information arrives sequentially to investors. He shows that volume, after all investors receive the information, is positively related to the magnitude of the price change.

4 The MDH provides theoretical reasoning here since it posits a joint dependence of returns and volume on an underlying latent event or information flow variable (Andersen, 1996). The contemporaneous relation between return volatility and trading volume can be derived at the daily level from a stylised microstructure framework in which informational asymmetries and liquidity needs motivate trade in response to the arrival of new information (Andersen, 1996). Cornell (1981) adds further evidence finding positive relations between changes in volume and changes in the variability of prices, each measured over two-month intervals, for each of 17 futures contracts. The relation was almost entirely contemporaneous, as most leading and lagged relations were statistically insignificant. Likewise, Rogalski (1978) found a contemporaneous correlation between price change and volume, but no lagged correlations.

5 A number of researchers have relaxed the weakly exogenous assumption by considering a lagged volume variable in the conditional variance equation (Najand and Yung, 1991).

6 The parameter space of the variance equation is constrained to be nonnegative.

7 Volume data on the UK stock market was not available from Datastream for Elan Corporation and Elan is therefore not included in this study.

8 Higher order GARCH models did not significantly increase the explanatory power of the conditional variance regression.

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