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IMPLIED STANDARD DEVIATIONS AND POST-EARNINGS ANNOUNCEMENT VOLATILITY ‡

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Abstract

This paper investigates volatility increases following annual earnings announcements. Standard deviations implied by options prices are used to show that announcements of bad news result in a lower volatility increase than those of good news, and delay the increase by a day. Reports that are difficult to interpret also delay the volatility increase. This delay is incremental to that caused by reporting bad news, although the effect of bad news on slowing down the reaction time is dominant. It is argued that the delays reflect market uncertainty about the implications of the news.

Keywords: Accounting news, implied volatility
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1 INTRODUCTION

The market effect of information reported in companies' earnings announcements is the subject of extensive research in the accounting and finance literature, stemming from the papers by Ball and Brown (1968) on stock returns, and Beaver (1968) on return volatility and trading volumes. Event studies based on stock returns focus primarily on the content of the announcement, testing the hypothesis that good (bad) news announcements are associated with positive (negative) returns, while volatility-based studies are more concerned with the clarity or precision of the reported information. One of the most robust findings of both strands of the literature is that the reactions to good and bad news are different. Announcements of bad news have generally been established to have lower earnings response coefficients (see Hayn (1995) for example); and in the financial econometrics literature it has been found that an asymmetric model, such as quadratic or exponential GARCH, fits the data better than one which does not distinguish between the two types of news (see Campbell and Hentschel (1992) and Engle and Ng (1993))[1].

Many theories have been proposed to explain the apparent under-reaction of stock returns to bad news and one common argument focuses on the transitory nature of negative earnings shocks (Hayn (1995), for example). More generally, Lipe et al (1998) investigate non-linearity in the earnings/returns relation, the existence of firm-specific earnings response coefficients and the under-reaction of returns to bad news, all of which

[1]To the extent that ex-post volatility represents risk that is priced in the market, there is clearly a connection between the reactions of post-announcement returns and volatility.

have been found in the literature. They postulate that these may simply be different manifestations of the same underlying characteristic, namely differences in earnings persistence. In fact, their test results show that all three have high incremental explanatory power in the earnings/returns model, so they do seem to be distinct phenomena.

This paper examines post-earnings announcement volatility, using implied standard deviations (ISDs) derived from option prices to establish the day-by-day changes in volatility within the announcement period. Unlike other studies in this area we focus primarily on the timing of the volatility increase, rather than on the level of the increase. The theoretical literature suggests that the relationship between the level of post-announcement volatility and the precision of the announcement is by no means clear-cut. Kim and Verrecchia (1991a and 1991b) and Abarbanell et al (1995), for example, argue that the relationship varies according to the characteristics of private information-gathering in the economy[2]. Consequently we avoid the problems of linking the level of volatility with announcement precision by concentrating instead on the related issue of uncertainty regarding the implications of the announcement, and the effect of uncertainty on the speed of the market's reaction to the news.

[2]Although empirical studies have established that volatility does increase around earnings announcements of all types, the interpretation of that rise is confused. Some writers, such as Donders and Vorst (1996), Ederington and Lee (1996) and Jayaraman and Shastri (1993), associate increased volatility with additional market uncertainty regarding the implications of the information. Others, such as Walmsley et al (1992), assume that increased volatility simply indicates that new information has reached the market.

We report below that the well-documented increase in volatility caused by earnings announcements occurs a day later for announcements of bad news than for announcements of good news[3]. Since uncertainty about the implications of new information is likely to delay the processing of that information, we would expect to see sluggish market reactions to announcements whose implications are relatively difficult to interpret. If this is the case, then the delayed reaction to bad news suggests that there is more uncertainty about the implications of bad news than the implications of good news. Following the argument in Lipe et al (1998), this may be because of the lower persistence of bad news, which means that they contain less information about future results than is contained in good news. Alternatively, it is possible that companies' reluctance to admit that the news is bad means that they try to diminish its impact by reducing the clarity of the information being announced.

Having established that there is a delayed reaction to bad news, we use a direct measure of earnings persistence to investigate the timing of the volatility reaction to news with a high transitory component. If our argument relating uncertainty to slower reaction times is valid, we would predict that announcements of earnings per share (eps) figures with a

[3]Although it is sometimes claimed, particularly in US-based studies, that companies reporting bad news often do so after the market closes, the Company Monitoring and Enquiries Office of the London Stock Exchange states that this could not happen in the UK without triggering an investigation. It is not possible to obtain details of exact timings of UK earnings announcements, but an extensive search of newspaper reports following the announcements in our sample revealed no evidence of bad news being delayed; and since the companies sampled were all high-profile, listed companies, it is unlikely that such delays would occur without comment in the press. Further, it is worth noting that delaying announcements in the US is facilitated by the existence of different regional time zones.

high transitory component, whose implications for the future are more difficult to assess, should be associated with a delayed volatility reaction. We categorise the announcements according to the standard deviation of the company's reported eps changes over the sample period, *SIGMAEPS*, and form portfolios based on this measure. Announcements by each firm are defined as having a high transitory component, and consequently as being relatively difficult to interpret, if the firm has a *SIGMAEPS* in the upper quartile of all the firms' *SIGMAEPS* [4]. As predicted, we find that the volatility reaction to high *SIGMAEPS* announcements is delayed.

We then proceed to examine whether the delayed reaction to bad news is a manifestation of their lower degree of earnings persistence, as encapsulated in the *SIGMAEPS* measure. We use OLS regression to examine the extent to which categorisation according to earnings surprise, or according to earnings persistence, each has incremental explanatory power for the observed pattern in post-announcement volatility.

We find that low *SIGMAEPS* announcements that are relatively easy to interpret, and announcements of good news, are each associated with a volatility peak on the day of the announcement itself. The volatility reactions to high *SIGMAEPS*, difficult-to-interpret news are delayed until the day after the announcement and the reactions to bad news are both delayed and suppressed; that is, the increase in volatility following bad news is generally lower than the increase following good news, taking into account both the day of the announcement and the following day.

[4] The portfolios are adjusted as described below to take account of other factors, such as profit warnings, which might affect the ease of interpretation of the announcement.

Announcing bad news and announcing news that is difficult to interpret both have an incremental effect on delaying the volatility reaction, but the effect of bad news appears to be dominant. The individual incremental effects lead us to conclude, as in Lipe et al (1998), that the two characteristics are not manifestations of the same underlying trait, although some information conveyed by the *SIGMAEPS* measure is contained in the sign of the news. This conclusion is reinforced by the suppression of volatility levels caused by bad news, which is not evident for difficult-to-interpret news. As discussed above, it may therefore be the case that companies reporting bad news deliberately convey less precise information, thereby extending the period required by the markets to analyse its implications.

In an efficient market, where prices quickly impound new information, we would expect the volatility reaction to an announcement to be relatively rapid and short-lived. The delay in the reaction to bad news suggests that, for whatever reason, the market is not efficient at processing such news. Companies announcing bad news should therefore be encouraged to improve the quality of information released, to help the markets in their assessment of the long-term implications of the announcement.

The rest of the paper is arranged as follows. Section 2 explains the methodology used for calculating the volatility changes around announcement dates. Section 3 discusses the data and section 4 presents descriptive statistics. Section 5 describes the OLS regressions and presents the results, and section 6 concludes the paper.

2 CALCULATING VOLATILITY CHANGES AROUND ANNOUNCEMENT DATES

The approach taken loosely follows the papers by Patell and Wolfson (henceforth PW) (1979) and (1981); similar techniques are used in Donders and Vorst (1996) and Ederington and Lee (1996).

In conditions of changing volatility, the ISD of an at-the-money option can be interpreted as an estimate of the expected standard deviation of the share return over the life of that option (Merton (1973) discusses deterministic volatility and Feinstein (1989) addresses the stochastic case)[5]. The ISD of the at-the-money option can therefore be used to analyse the pattern of volatility which the market expects to occur around an announcement. As a simple example, assume that the ISD of an option with a life of, say, 20 days equals the simple average of anticipated daily standard deviations of share returns over those 20 days. Also suppose that the (annualised) daily standard deviation is expected to be 0.3, except during day 10, when it is expected to double to 0.6. The ISD of the option will be as shown in figure 1. If the day of the anticipated volatility increase is known, then by measuring the ISD at two points before that day, the 'basic' volatility and the amount of the increase can be deduced.

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[5]Feinstein points out that many stochastic volatility pricing models result in an option price which equals the expected Black Scholes (BS) (1973) model price over the life of the option. He argues that since the BS price of an at-the-money option is linear with respect to standard deviation, the stochastic model prices reduce to the BS price evaluated with the instantaneous standard deviation replaced by the expected volatility over the life of the option. However, Bates (1995) notes that since the expectation in the stochastic volatility models is taken over average variance, not standard deviation, the relationship does not hold exactly. Nevertheless the error is small (see, for example, Heynen et al (1994), who show empirically that the relationship is accurate for various models such as Hull and White (1987), which is based on a mean-reverting volatility process, and Duan (1995), which deals with GARCH and exponential GARCH processes).

FIGURE 1 ABOUT HERE

The PW approach is based on this example. They hypothesise that the instantaneous volatility of the share return is, and is expected to be, γ, except for during an 'announcement period' which begins at time t_0 and lasts for τ days. During this period the instantaneous volatility is expected to rise by an amount δ, so that the average volatility over the life of an option which expires at time $t_e > t_0$, equals $\gamma + \tau\delta / (t_e - t_a)$, where t_a is the date at which the volatility is observed. PW use this equation to develop three measures to assess the nature of the expected change in instantaneous volatility over the announcement period.

Two refinements can be applied to the PW model. One is an adjustment to reflect the term structure of volatilities which has been identified by other authors (such as Heynen et al (1994); Xu and Taylor (1994)). PW acknowledge that the "presence of an underlying secular trend in implied variance estimates may alter the specification of the model of anticipated information content" (p 449). It is clear that if an existing trend is ignored the wrong inferences may be drawn from inter-day changes (or lack of changes) in ISDs. We allow for the presence of an underlying trend by assuming that the instantaneous (annualised) volatility is expected to change by an amount η each day. At the start of the test period the basic volatility, excluding the effect of expected changes due to the announcement, equals γ. (η may be positive or negative and γ and η are firm-specific.)

The second adjustment to the PW model is to recognise that the expected effect on volatility of an announcement may not be a simple rise during the announcement period. In fact, the duration and timing of the announcement period itself is not certain. Volatilities may be expected to change immediately before the announcement as well as after it and the whole period around the announcement may be expected to show a more complex pattern of changing volatilities.

The model used here assumes that volatilities may be affected for 20 days around the announcement, with more frequent changes expected in the ten-day period around the announcement. Clearly the assumption is ad hoc and probably overestimates the frequency of anticipated changes in volatility. However, if no change is actually anticipated by the market at any particular date, the calculations described below will reflect that, by generating results which are not significantly different from zero.

Figure 2 shows hypothetical (firm-specific) changes in instantaneous volatility over the 20-day period surrounding the announcement. The increment at the beginning of day λ is denoted as δ_λ, where λ = -9, -4, -1, 0, 1, 2, 3, 6, 11. For periods longer than one day, λ represents the first day of the period, so, for example, the first increment is δ_{-9}, which is the change in volatility at the beginning of days -9 to -5 inclusive. The next change, δ_{-4}, occurs at the beginning of days -4 to -2 inclusive; and so on. The announcement occurs during day 0. As shown, we assume that, ignoring the possible secular trend, there is reversion to the basic long-term level, γ, at the end of day 10. A model was also tested which allowed long-term volatility to settle at a new level after the announcement, but, as discussed below, the results suggested that there was no significant change in long-term volatility following announcements. Volatility is shown in figure 2 as peaking on the announcement day, but whether or not it does is the subject of the tests reported below. The figure also sets η at zero, for the purposes of illustration only.

FIGURE 2 ABOUT HERE

Putting together the term structure changes and the expected volatility changes, a set of equations can be derived for the average volatility, and therefore, by assumption, the implied volatility at each of the dates given above. The aim is to use implied volatilities from observed options prices at the given dates to solve these equations for δ_λ, γ and η. The assumption of reversion to γ at the end of day 10 means that we need to calculate only eight of the nine ‘δ increments’, since one of them will equal γ minus the sum of the others. We therefore have a total of ten unknowns requiring ten equations for their solution. Implied volatilities were estimated for the start of each of the ten periods/days shown in figure 2 (although since data was available only for the **close** of each trading day, the calculations were done by reference to option and share prices at the end of the day immediately preceding the period/day in question). A date was needed for the start of earliest period shown in figure 2, which is unlabelled, as it represents the pre-event period. A date of t = -25 was chosen, again an ad hoc choice. This was set as the start of the test period, so that at t = -25 the basic volatility, excluding announcement effects, equals γ (so at t = -24, for example, it equals γ + η, and so on).

The equations for average volatility are as follows:

$$\begin{aligned}\bar{V}_{-25} &= \gamma + \tfrac{1}{2}\eta\left(T_{-25} + \tfrac{1}{365}\right) + \\ &\tfrac{1}{T_{-25}}\Big(\left(T_{-10} - T_{10}\right)\delta_{-9} + \left(T_{-5} - T_{10}\right)\delta_{-4} + \left(T_{-2} - T_{10}\right)\delta_{-1} + \left(T_{-1} - T_{10}\right)\delta_{0} + \\ &\left(T_{0} - T_{10}\right)\delta_{1} + \left(T_{1} - T_{10}\right)\delta_{2} + \left(T_{2} - T_{10}\right)\delta_{3} + \left(T_{5} - T_{10}\right)\delta_{6}\Big)\end{aligned} \tag{1}$$

$$\begin{aligned}\bar{V}_{-10} &= \gamma + \tfrac{1}{2}\eta\left(2T_{-25} + \tfrac{1}{365} - T_{-10}\right) + \\ &\tfrac{1}{T_{-10}}\Big(\left(T_{-10} - T_{10}\right)\delta_{-9} + \left(T_{-5} - T_{10}\right)\delta_{-4} + \left(T_{-2} - T_{10}\right)\delta_{-1} + \left(T_{-1} - T_{10}\right)\delta_{0} + \\ &\left(T_{0} - T_{10}\right)\delta_{1} + \left(T_{1} - T_{10}\right)\delta_{2} + \left(T_{2} - T_{10}\right)\delta_{3} + \left(T_{5} - T_{10}\right)\delta_{6}\Big)\end{aligned} \tag{2}$$

etc....; and

$$\bar{V}_{10} = \gamma + \tfrac{1}{2}\eta\left(2T_{-25} + \tfrac{1}{365} - T_{10}\right), \tag{3}$$

where $\bar{V}_t$ is the average volatility over the life of the option, as at the end of day *t*; and

T_t is the time to expiry of the option (as a fraction of a year), as at the end of day *t*.

These equations were used to derive equations for the ten unknowns, which were then applied to the observed implied volatilities to calculate δ_λ, γ and η for each sampled announcement. The difference between the instantaneous volatility at the end of each day and the usual volatility level, Δ_λ, was also calculated by summing the daily volatility increments: $\Delta_\lambda \equiv \sum_{\Lambda=-9}^{\lambda} \delta_\Lambda$, where Λ = -9, -4, -1, 0, 1, 2, 3, 6 and λ is as defined above (so $\Delta_{-9} = \delta_{-9}$. Note also that $\Delta_{11} = 0$).

One issue to resolve is whether to measure volatility in terms of variance or standard deviation. PW use standard deviations in their tests. Both measures were tried (with implied variances calculated as ISDs squared) but only results based on ISDs are reported, primarily because using variances exacerbates the problems caused by outliers. The results using variances were not qualitatively different from those using standard deviations.

As mentioned above, a slightly different version of the model was also tested. The tests reported below found that η, the time structure increment, was not significant, so a second version of the model set $\eta = 0$, and assumed instead that after day 10 long-run, basic volatility moved to a new level, $(\gamma + \Gamma)$ [6]. It turned out that Γ tended to be slightly negative, but also not significant. Only results based on the first version of the model are reported. The second version produced qualitatively similar results.

[6]The replacement of one apparently insignificant unknown, η, with another, Γ, avoided the time-consuming task of collecting more data.

3 THE DATA

3.1 Sample selection

Firms in the UK's FTSE 100 with options quoted on their shares between November 1989 and October 1996 were identified and the final earnings announcements of the firms over this period were chosen as the sample of announcements to be tested. The sample was reduced by removing insurance companies, which have their own rules for reporting earnings, and British Gas, which publishes historic and current cost accounts and changed its year end during the sample period, thereby introducing ambiguity about which results should be used in tests.

Final earnings announcement dates were identified using Extel cards and news sheets, each announcement being treated as a separate observation. Observations involving changes in year-ends were dropped, since these complicate the comparison between two consecutive sets of financial statements. The Extel news sheets were also used to identify when companies issued profit warnings.

The final sample size was 379 final announcements made by 60 companies, with ISDs estimated at ten points in each announcement period (a total of 3,790 ISDs).

3.2 Options data

Trades in the call option closest to the money during each announcement's test period were identified. The relevant data (option price at close of trading, underlying price at close of trading, exercise price and time to expiry) were obtained from the London International Financial Futures and Options Exchange (LIFFE), which provides a CD ROM covering the period beginning 23 March, 1992, when LIFFE took over from the London Traded Options Market. Earlier data were extracted manually from the market reports in the Financial Times newspaper. If there were two options equally near to the money, they were both included in the sample and a simple average was taken of their ISDs. The earliest expiring option was selected, as long as it expired more than five trading days after the end of the test period[7] (ISDs tend to exhibit unusual patterns when the option is close to expiry). The one-month Treasury bill rate on the trade date as reported in Datastream was used as the risk-free rate. Dividends paid on underlying shares and the ex-div dates were obtained from Datastream and Extel cards.

3.3 Calculation of ISDs

The ISDs of the sampled options were estimated using the Roll (1977); Geske (1979), (1981); Whaley (1981) - henceforth RGW - model, which extends the Black Scholes (1973) model to valuation of American call options on dividend-paying shares. The RGW model recognises the fact that under certain conditions it may be worth exercising these options early, just before the underlying share goes ex-div, so that the price of the option may include an early exercise premium.

3.4 Analysts' forecasts

Details of analysts' earnings per share (eps) forecasts for each announcement were obtained from the Institutional Brokers Estimate System (I/B/E/S) database, together with the actual eps results corresponding to the forecasts (I/B/E/S adjusts reported results to the same basis on which the forecasts are made).

[7]The sample's mean and median times to expiry as at the announcement date were just over two months, ranging between 0.7 and 4.2 months.

3.5 Reported earnings per share

Although Datastream item 254 gives ‘reported’ eps figures, these are not always suitable for comparing annual eps figures as actually reported (even allowing for adjustments following capital issues), due to changes in accounting policies and prior year adjustments. This is particularly true on the introduction of Financial Reporting Standard (FRS) 3, *Reporting Financial Performance*. Extel news sheets and, in some cases, the annual reports themselves, were used to establish the eps figure actually reported in each announcement, together with the reported comparative figure. For post-FRS3 reports, the FRS3 eps figure was used (that is, the one stated after accounting for extraordinary items - many companies now report several different eps figures on the face of the profit and loss account).

3.6 Portfolio construction

The first criterion for portfolio formation was the sign of the earnings surprise, where the surprise was defined as the difference between the I/B/E/S mean forecast and actual eps. The second criterion was based on the standard deviation of the company’s reported eps changes over the sample period, *SIGMAEPS*, as explained in the introduction. Announcements were defined as having a high transitory eps component, and therefore as being relatively difficult to interpret, if the firm had a *SIGMAEPS* in the upper quartile of all the firms’ *SIGMAEPS* [8]. All other announcements were defined as having a low

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[8]Ideally, a historic eps standard deviation should be calculated for each announcement, by considering a period, five years, say, preceding the announcement. However, the Datastream eps data were generally not available before 1988 (and the sample period began in 1989), so eps figures collected from Extel were used as described below, to calculate a within-sample standard deviation for each firm, under the assumption that current period standard deviation is a good proxy for earlier periods’ standard deviation. Each announcement by the firm was allocated with the firm’s eps standard deviation.

transitory component, and therefore as being relatively easy to interpret. The portfolios were adjusted to take account of other variables which might affect the ability of the market to interpret the earnings information. Six announcements which were the first or second announcements by newly created companies were reassigned to the difficult-to-interpret category, although they had low *SIGMAEPS* measures, since eps announcements made at this stage of a firm's life are likely to require longer processing time. Four announcements by high *SIGMAEPS* firms were preceded by profit warnings from the firms, so some information in the eps announcement could be processed before the announcement itself (all of these observations had non-zero surprises, so the warnings did not fully reveal the information in the final announcement). These were assigned to the easy-to-interpret category.

The numbers of observations in each portfolio are given in table 1, which shows that there is a fairly even distribution of high *SIGMAEPS* announcements between the good and bad news observations. As mentioned above, it is interesting to note that there are more good news than bad. The proportion of positive surprises in the sample is 56% and a sign test of whether this proportion is significantly higher than 50% has a t-statistic of 2.311, which is significant at just above the 1% level.

TABLE 1 ABOUT HERE

4 DESCRIPTIVE STATISTICS

The ISDs over the announcement period are summarised in table 2. As expected, the ISDs tend to rise before the announcement date and fall after it, which is consistent with an expected increase in volatilities during the announcement day itself. The day 10 ISDs suggest that volatility rises again roughly two weeks after the announcement, but as discussed above, tests on the version of the model which allowed for a permanent change in long-term expected volatility indicated that any change was not statistically significant.

TABLE 2 ABOUT HERE

Table 3 presents, for the good and bad news portfolios, summary statistics for the basic volatility (γ), the time structure increment (η) and the announcement-induced changes in volatility. The table includes *t*-statistics for the means based on their standard errors, and the results of Wilcoxon matched pairs signed ranks tests on the means, which were used to test whether the *t*-statistics were unduly influenced by outliers. Since the signs and degree of significance of the Wilcoxon test statistics match those of the *t*-statistics, the skewness of the distribution is unlikely to be significantly distorting the results. Figure 3 compares the means of the good and bad news' volatility changes pictorially.

TABLE 3 AND FIGURE 3 ABOUT HERE

Table 3 shows that the means of the basic volatilities (γ) are highly significant, confirming that the methodology outlined in section 2 generates reliable volatility estimates. The term structure increments are not significant at conventional levels, suggesting that adjustment for term structure effects over a short period is not important.

As far as the volatility increments are concerned, both the means and the medians suggest that there is a peak in volatility on day 0 for good news announcements but on day +1 for bad news announcements. This was confirmed by F-tests which showed that Δ_0 is significantly higher for good news than for bad news (*p*-value of 0.18%); while Δ_1 is significantly higher for bad news than for good (*p*-value of 0.53%). Furthermore, the change in volatility between the end of day 0 and the end of day 1 (δ_1 in figure 2) is significantly negative for good news (the mean has a *t*-statistic of -3.090 and the Wilcoxon Z-statistic is -3.743) and significantly positive for bad news (*t*-statistic 2.378, Wilcoxon statistic 1.809).

The other interesting feature, which is not the direct concern of this study so is not discussed further, is the dip in volatility which occurs in the few days before and after the announcements other than the immediate period surrounding the announcement. The Δ_{-4}s (relating to period (-4, -2)), and the Δ_3s and Δ_6s (relating to period (3, 10)) are negative and, other than the bad news' Δ_3, significant at conventional levels. A similar dip is noted in Donders and Vorst (1996); and DeGennaro and Shrieves (1997), working with high frequency data, also find reductions in volatility in the two hours preceding, and the twenty minutes following, certain macroeconomic announcements.

In the interests of space, data relating to the 14 zero-surprise, 'no news' announcements are not shown. For these announcements, the only variable which was significant at standard levels was γ: as might be expected when there is no news, volatility did not appear to change significantly around the announcement. The most significant volatility increment was Δ_0, which had mean of 1.086 with a *t*-statistic of 1.822 (a *p*-value of 0.07), indicating some increase in volatility on the day of the announcement, but of a far lower significance than that of the good news observations.

The descriptive statistics for the *HISIGMA* and *LOSIGMA* portfolios showed similar patterns, so are not reported here. The *HISIGMA*, difficult-to-interpret news appear to have volatility peaks on the day after the announcement, while the *LOSIGMA*, easy-to-interpret news have volatility peaks on the day of the announcement itself.

5 REGRESSION ANALYSIS

The data presented above suggest that there is a peak in volatility on the day of the announcement of good news, and a smaller peak on the following day if the news is bad. As discussed above, we wish to examine whether the asymmetry in the reactions to good and bad news is a result of the transitory nature of the bad news, which makes its implications for the future more difficult to assess. We use OLS regression to establish whether our measure of earnings persistence contains information incremental to that contained in the sign of the news. The OLS models also control for other relevant independent variables, as discussed in the following paragraphs.

It is generally argued that the higher the quality of pre-announcement information, the lower will be the post-announcement volatility (see for example Kim and Verrecchia (1991a, 1991b) and Abarbanell et al (1995)), so one would expect the volatility increments to be negatively related to whichever proxy is chosen for this variable. As in other studies (see for example Bajaj and Vijh (1995)), we used as our proxy the market value of the firm ten days before the announcement. Since the observations extended over a seven year period the market value had to be standardised, so it was divided by the value of the FTSE 100 index at the time of measurement, to give an adjusted market value, *MV*.

A second variable which might be expected to affect volatility around the announcement period is the level of basic volatility, γ. It is sometimes argued that a high level of volatility is indicative of the frequent arrival of new information about the company, in which case γ is positively related to pre-announcement information quality and should be negatively related to the volatility increments. Alternatively, volatility is often seen as synonymous with uncertainty (see footnote 2), in which case the predicted relationships would be reversed. The sign of γ in the regression equations will therefore provide an incidental test of these competing hypotheses.

We began by estimating equation (4), to confirm that the volatility peaks do indeed occur on days 0 and 1 of the announcement period (all OLS equations described below were estimated using White's heteroskedastic-consistent covariance estimator).

$$\Delta_k = \alpha + \beta_\lambda DUM_{\lambda,k} + \phi\left(MV_k \times POST_{\lambda,k}\right) + \varphi\gamma_k + \mu_k, \qquad \lambda = -4, -1, 0, 1, 2, 3, 6 \qquad (4)$$

where Δ_k are the volatility increments for the period around announcement k;

α, β_λ, ϕ and φ are regression coefficients to be estimated;

$DUM_{\lambda,k}$ are dummy variables which take the value 1 if the increment applies to day/period λ, and 0 otherwise;

MV_k is the adjusted market value of the firm ten days before announcement k (firm subscript omitted for clarity);

$POST_{\lambda,k}$ is a dummy variable which takes the value 1 if day/period λ ends after the announcement (i.e. λ = 0, 1, 2, 3, 6), so that $MV_k \times POST_{\lambda,k}$ measures the relationship between *MV* and post-announcement volatility changes[9];

γ_k is the basic level of volatility preceding the announcement; and

μ_k is an error term.

In equation (4) Δ_{-9} is taken as the 'basic' volatility increment, with the dummies DUM_λ identifying increments measured at other times over the announcement period[10]. The regression coefficients therefore identify the periods/days in the announcement period which have volatility levels that are significantly different from usual, while controlling for the independent variables discussed above. (Zero-surprise observations were omitted from this and subsequent OLS estimations.)

[9]We initially tried including *MV* for pre-announcement increments, but it was not significantly different from zero. This confirms the joint hypotheses that *MV* is a good proxy for the quality of pre-announcement information and that pre-announcement information affects post-announcement volatility.

[10]This means that Δ_{-9} cannot be distinguished from the noise in the estimation, but this study is primarily concerned with Δ_0 and Δ_1, the increments on the day of, and the day after, the announcement, so this is not a significant problem.

The results of the regression are given below (t-statistics in parentheses; * = significant at 5%; ** = significant at 1% (two-tailed)):

$$\begin{array}{llllll}
\Delta_k = & 0.176 & -\ 0.096\ DUM_{-4} & +\ 0.028\ DUM_{-1} & +\ 0.467\ DUM_0 & +\ 0.288\ DUM_1 \\
 & (2.709)^{**} & (-2.345)^{*} & (0.316) & (4.004)^{**} & (2.674)^{**}
\end{array}$$

$$\begin{array}{lllll}
+\ 0.039\ DUM_2 & +\ 0.005\ DUM_3 & +\ 0.015\ DUM_6 & -\ 0.030\ MV & -\ 0.715\ \gamma \\
(0.593) & (0.121) & (0.426) & (-2.214)^{*} & (-3.067)^{**}
\end{array}$$

$R^2 = 0.030$

The results confirm the picture suggested by the descriptive statistics, that there is a peak in volatility at the ends of days 0 and 1 (DUM_0 and DUM_1), the day 0 peak being larger and more significant. The pre-announcement dip noted earlier is also evident, with a significantly negative DUM_{-4}, but the post-announcement dip is not. As predicted, MV is significantly negative. It is shown below that MV is not important in explaining Δ_0, the difference between immediate post-announcement volatility and normal volatility levels, but it becomes more significant in explaining δ_1, the change in volatility between days 0 and 1. It may be that the quality of pre-announcement information has a slightly delayed effect on the volatility reaction, so that the post-announcement dip shown in the descriptive statistics relating to the Δ_3s and Δ_6s is soaked up by including MV in the regression analysis.

γ is strongly negative, which suggests that the first of the propositions outlined above is valid: a high level of volatility reflects the frequent arrival of new information regarding the company, and ‘normal’ volatility is therefore a suitable proxy for the quality of a firm’s information environment.

For the more detailed analysis of the relationships among post-announcement volatility, news type and earnings persistence, we estimated the set of OLS equations (5a) to (5d).

$$\Delta_{0,k} = \mathrm{A} + \mathrm{B}BAD_k + \mathrm{G}\gamma_k + \mathrm{H}MV_k + \varepsilon_k \quad (5a)$$

$$\Delta_{0,k} = \mathrm{A} + \mathrm{C}HI_k + \mathrm{G}\gamma_k + \mathrm{H}MV_k + \varepsilon_k \quad (5b)$$

$$\Delta_{0,k} = \mathrm{A} + \mathrm{B}BAD_k + \mathrm{C}HI_k + \mathrm{G}\gamma_k + \mathrm{H}MV_k + \varepsilon_k \quad (5c)$$

$$\Delta_{0,k} = \mathrm{A} + \mathrm{D}BADHI_k + \mathrm{E}BADLO_k + \mathrm{F}GOODHI_k + \mathrm{G}\gamma_k + \mathrm{H}MV_k + \varepsilon_k \quad (5d)$$

where $\Delta_{0,k}$ is the difference between normal volatility levels and volatility at the end of the day of announcement *k*;

A, B, C, ..., H are regression coefficients to be estimated;

BAD_k is a dummy variable which takes the value 1 if the news is bad (actual eps lower than mean forecast);

HI_k is a dummy variable which takes the value 1 if the announcement is in the high *SIGMAEPS* portfolio;

$BADHI_k$ is a dummy variable which takes the value 1 if the news is bad and is in the high *SIGMAEPS* portfolio;

$BADLO_k$ is a dummy variable which takes the value 1 if the news is bad and is in the low *SIGMAEPS* portfolio;

$GOODHI_k$ is a dummy variable which takes the value 1 if the news is good and is in the high *SIGMAEPS* portfolio;

γ and *MV* are defined above; and

ε_k are error terms.

Equations (5a) and (5b) identify the incremental effects on immediate post-announcement volatility of announcing bad news or an eps figure which is difficult to interpret, respectively. The descriptive statistics reported above suggest that the *BAD* dummy should have a significantly negative coefficient, as bad news announcements are associated with volatility reactions on the day after than the announcement, rather than the day of the announcement itself. Similarly the descriptive statistics on the easy-/difficult-to interpret portfolios lead us to expect a significantly negative coefficient on *HI*.

Equation (5c) examines whether each of the categorisation criteria carries incremental information. In particular, if the reaction to bad news is connected with the low persistence of the reported eps, we would expect the coefficients on *BAD* or *HI* in this equation to fall in significance.

Finally equation (5d) allows for interaction between the announcement categories. The 'basic' observations are announcements of good news which are in the low *SIGMAEPS* portfolio. The dummies identify the incremental effects on volatility of bad news announcements which are in the low or high *SIGMAEPS* portfolios respectively; and good news announcements in the high *SIGMAEPS* portfolio. If bad news is essentially a proxy for low earnings persistence, we would expect all the dummies to be equally significantly negative, since either bad news, or high *SIGMAEPS*, or both would be indicators of the same underlying characteristic.

Table 4 gives the regression results. Although neither γ nor *MV* are significant explanators for the $\Delta_{0,k}$s, they are more important in the second set of regressions which are described below. We therefore retained them in equations (5) for the purposes of comparison. They are discussed in more detail below.

TABLE 4 ABOUT HERE

The results for equations (5a) and (5b) in table 4 show that both bad news and difficult-to-interpret news depress the volatility reaction, although the fact that the news is bad seems to have a stronger effect than the fact that the information is hard to interpret, since *BAD* has a more negative and more significant coefficient than does *HI* in these equations. Equation (5c) shows that the two variables each contain incremental information, suggesting that they are not manifestations of the same underlying characteristic, but again *HI* seems less important than *BAD*, with a smaller and less significant coefficient. This pattern is repeated in equation (5d). For bad news announcements, the coefficient on the dummy for difficult-to-interpret news (*BADHI*) is 0.827 higher in absolute terms than that for easy-to-interpret ones (*BADLO*). A test of whether the difference between these coefficients is significant had a *t*-statistic of 1.646 (*p*-value 0.05). Announcing information which is difficult to interpret therefore increases the extent to which the reaction is suppressed, but does not have as strong an effect as announcing bad news. Furthermore, although the dummy for difficult-to-interpret, good news announcements (*GOODHI*) does have a negative coefficient, it is not significant at conventional levels. For good news announcements, the fact that the news is good appears to dominate the fact that the information is difficult to interpret.

The suppression of the volatility peak was further examined by estimating a second set of equations, (6a), to (6d), which have as their dependent variable $\delta_{1,k}$, the change in volatility between the end of the day of announcement k and the end of the following day.

$$\delta_{1,k} = \mathrm{A} + \mathrm{B}BAD_k + \mathrm{G}\gamma_k + \mathrm{H}MV_k + \mathrm{I}GOOD\Delta_{0,k} + \mathrm{J}BAD\Delta_{0,k} + \varepsilon_k \quad (6a)$$

$$\delta_{1,k} = \mathrm{A} + \mathrm{C}HI_k + \mathrm{G}\gamma_k + \mathrm{H}MV_k + \mathrm{I}GOOD\Delta_{0,k} + \mathrm{J}BAD\Delta_{0,k} + \varepsilon_k \quad (6b)$$

$$\delta_{1,k} = \mathrm{A} + \mathrm{B}BAD_k + \mathrm{C}HI_k + \mathrm{G}\gamma_k + \mathrm{H}MV_k + \mathrm{I}GOOD\Delta_{0,k} + \mathrm{J}BAD\Delta_{0,k} + \varepsilon_k \quad (6c)$$

$$\begin{aligned}\delta_{1,k} = {} & \mathrm{A} + \mathrm{D}BADHI_k + \mathrm{E}BADLO_k + \mathrm{F}GOODHI_k + \mathrm{G}\gamma_k + \mathrm{H}MV_k \\ & + \mathrm{I}GOOD\Delta_{0,k} + \mathrm{J}BAD\Delta_{0,k} + \varepsilon_k \end{aligned} \quad (6d)$$

The independent variables in these equations are the same as those in the set of equations in (5), except that $GOOD\Delta_{0,k}$ and $BAD\Delta_{0,k}$ have been added. These are the dependent variable in equations (5), $\Delta_{0,k}$, split between good news and bad news announcements and are included to account for the tendency to revert to normal volatility levels. We therefore expect the coefficients to be significantly negative for good news announcements and less strongly negative for bad news ones, reflecting the delayed volatility reaction.

The coefficients on the *BAD*, *HI*, *BADHI*, *BADLO* and *GOODHI* dummies will establish the extent to which reactions to bad and *HISIGMA* news are delayed rather than suppressed. If the reaction is simply delayed, we would expect to see positive coefficients of roughly equal magnitude and significance as in the equivalent equations in table 4. If the reactions are suppressed, rather than just delayed, we would expect these coefficients to be non-positive. Significantly negative coefficients would indicate that the suppression of the reaction continues over two days, while coefficients that are not significantly different from zero would suggest that only the day 0 reaction to bad/*HISIGMA* news is lower than for other news.

Table 5 gives the regression results. As noted above, neither γ nor *MV* were significant in equations (5), but they are more important explanators of the $\delta_{1,k}$ in equations (6). Both variables have negative coefficients in all the models (including equations (5)), although *MV* is only significant at conventional levels in equation (6a). Assuming that they are good proxies for pre-announcement information - which in the case of γ is confirmed by its negative coefficient, as in equation (4) and the ensuing discussion - this suggests that the immediate volatility reaction to an announcement is not substantially affected by pre-announcement information quality; but that the subsequent re-adjustment is.

TABLE 5 ABOUT HERE

The other coefficients suggest that the volatility reaction to bad news is both delayed and suppressed, while the difficult-to-interpret news reaction is simply delayed. The *BAD* dummies in equations (6a) and (6c) do have positive coefficients, but they are smaller in absolute value and less significant than the corresponding negative coefficients in equations (5a) and (5c). This indicates that some, but not all, of the difference between good and bad news reactions is made up on the day after the announcement. Conversely, the *HI* dummies in equations (6b) and (6c) have positive coefficients roughly equal in size and significance to the corresponding ones in equations (5b) and (5c), suggesting that the difference between reactions to easy- and difficult-to-interpret news is completely reversed on the day after the announcement. In equation (6d) the coefficients on *BADHI*, *BADLO* and *GOODHI* reflect combinations of these effects.

As predicted, the coefficients on $GOOD\Delta_0$ and $BAD\Delta_0$ are strongly negative, and the latter are smaller in absolute value, although they are more statistically significant. This supports the proposition that there is reversion to some long-term norm in the volatility-generating process, as discussed above and as assumed in the original model.

6 CONCLUSION

This paper examines the links between the type of earnings information reported and the timing of the volatility reaction to that information.The tests on volatility changes around announcements indicate that announcements that are easy to interpret or announcements of good news are both associated with a volatility peak on the day of the announcement itself. The volatility reactions to bad and difficult-to-interpret news are delayed until the day after the announcement. The reactions to bad news are also suppressed; that is, the increase in volatility following bad news is generally lower than the increase following good news, taking into account both the day of the announcement and the following day. Reporting bad news and reporting information that is difficult to interpret each has an incremental effect on delaying the volatility reaction to the news, but the effect of announcing bad news appears to dominate the effect of announcing news that is difficult to interpret.

Following the arguments in Lipe et al (1998), the question posed at the outset was whether the difference between the volatility reactions to good and bad news arose because a negative surprise is seen as more transitory in nature than a positive one, leading to difficulties in interpreting the long-term implications of the news. If this were the case, one would not expect both the sign of the news and the proxy for the difficulty of interpretation of the news to have incremental explanatory power in the regression models. They did have incremental explanatory power so, as in Lipe et al (1998), we conclude that the two characteristics are not manifestations of the same underlying characteristic. Negative surprises occur less frequently than positive ones, so it is possible that the delayed reaction to bad news may be partly due to their 'rarity' value. Alternatively, it may be that companies announcing bad news deliberately try to diminish the impact of the news by reducing the clarity of the information presented.

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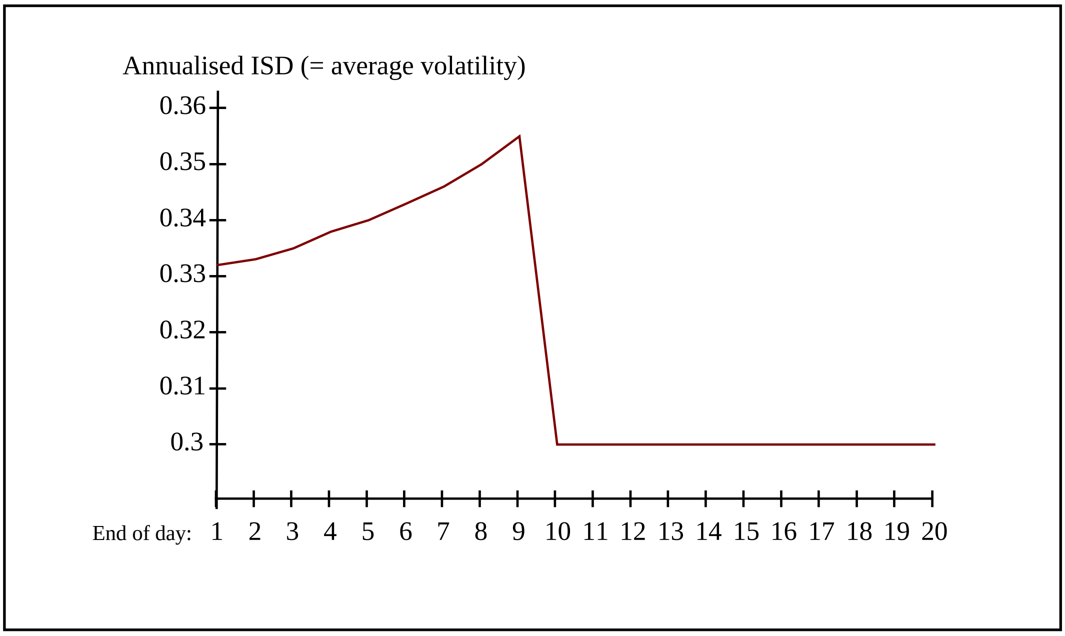
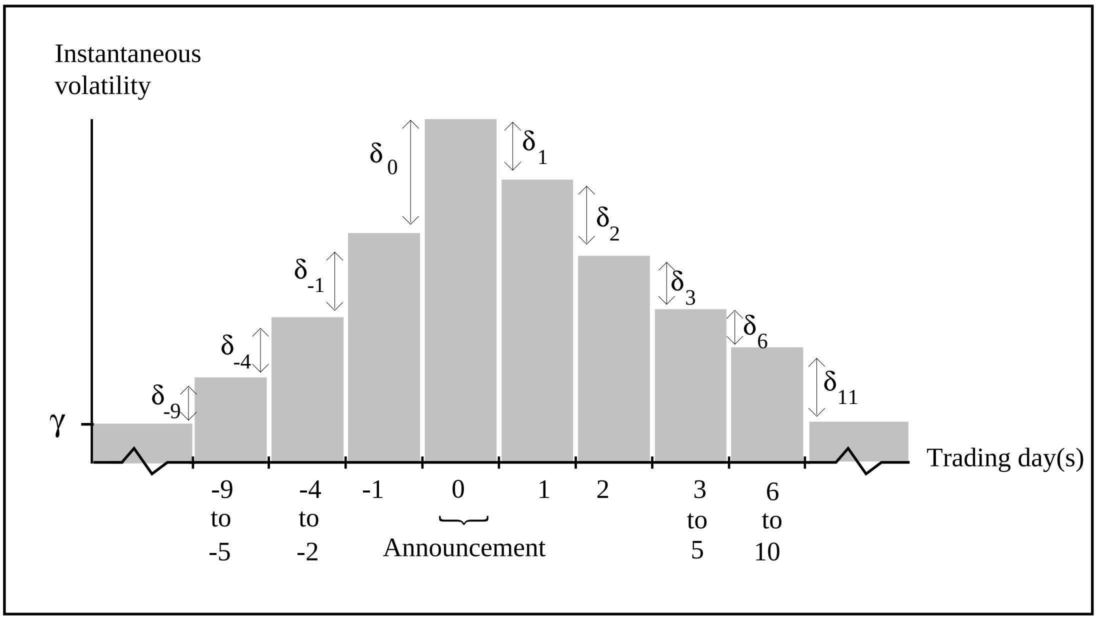
Figure 1 Annualised ISD with anticipated increase in volatility during day 10



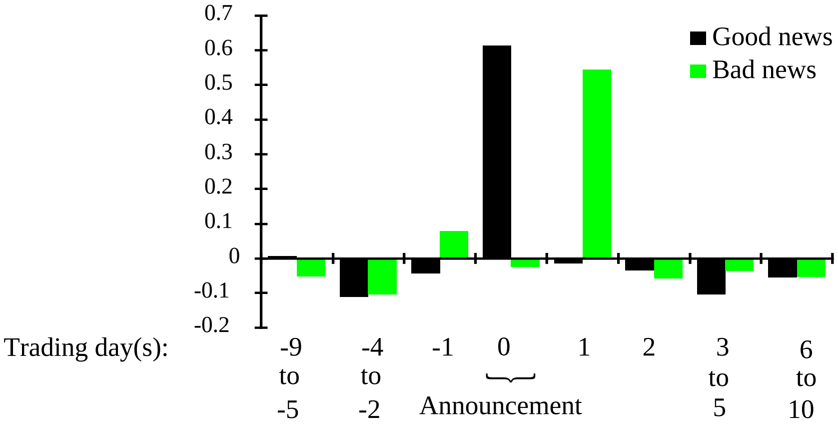
The figure shows the ISD of an option with 20 days to expiry, where the ISD equals the (annualised) mean daily standard deviation of the underlying share return over the life of the option, and the daily standard deviation is expected to be 0.3, except during day 10, when it is expected to double to 0.6.

Figure 2 Expected changes in instantaneous volatility during the announcement period



The figure shows the hypothesised changes in instantaneous volatility around the announcement day (day 0). Long-term 'basic' volatility is γ and any underlying trend in volatility is ignored, for simplicity. The change in volatility at the beginning of each period/day is denoted as δ_λ, where λ = -9, -4, -1, 0, ..., 11. For simplicity, volatility is shown to increase up to the end of the announcement day and then revert to its long-term level; the tests reported below do not constrain any increment to be negative or positive.

Figure 3 Mean volatility changes ignoring term structure effects



The figure shows the mean changes in volatility around the announcement date, for the two categories of good news (positive earnings surprise) and bad news (negative earnings surprise) portfolios

Table 1 Portfolio categories

	Good news (positive surprise)	**Bad news (negative surprise)**	**No news (zero surprise)**
Total	212	153	14
LOSIGMA firms *(b, c)*	170	123	9
HISIGMA firms *(b, c)*	42	30	5
	212	153	14

Notes

a. The table summarises the number of announcement types in each category within the portfolios of good and bad news (positive and negative earnings surprises). A positive (negative) surprise arises when the reported earnings per share (eps) exceeds (is less than) the mean forecast eps.

b. 'LOSIGMA' and 'HISIGMA' categorise announcements according to the standard deviation of the announcing firm's changes in reported eps over the sample period ('SIGMAEPS'). 'LOSIGMA' denotes announcements made by firms with a SIGMAEPS which lies in the lower three quartiles of the distribution of all firms' SIGMAEPS. These announcements have high earnings persistence and are relatively easy to interpret. 'HISIGMA' denotes all other announcements, that is, those with low earnings persistence, which are relatively difficult to interpret.

c. Announcements which were the first or second announcements made by newly created companies were assigned to the HISIGMA category, regardless of the firm's SIGMAEPS. Announcements which followed profit warnings made by the announcing company were assigned to the LOSIGMA category, regardless of the firm's SIGMAEPS.

Table 2 Implied standard deviations

Day relative to announcement day	Mean	Median	Standard deviation	Minimum	Maximum
-25	0.258	0.235	0.083	0.085	0.713
-10	0.255	0.235	0.088	0.112	0.973
-5	0.256	0.237	0.090	0.087	0.934
-2	0.263	0.238	0.102	0.079	0.983
-1	0.263	0.238	0.101	0.088	0.998
0	0.255	0.233	0.094	0.077	1.077
1	0.251	0.228	0.095	0.121	1.140
2	0.251	0.229	0.091	0.118	1.059
5	0.257	0.232	0.095	0.117	0.946
10	0.264	0.237	0.099	0.128	1.017

The table shows details of the implied standard deviations of the whole sample around the announcement period

Table 3 Basic volatility and increments in volatility

	Trading days	Good news					Bad news				
		Mean	Median	Std. dev.	Minimum	Maximum	Mean	Median	Std. dev.	Minimum	Maximum
γ		0.270	0.247	0.185	-0.544	1.162	0.276	0.233	0.211	-0.695	1.186
		(21.076)** (12.205)**					(15.931)** (10.204)**				
η		-0.000	0.000	0.003	-0.013	0.014	-0.000	0.000	0.003	-0.011	0.014
		(-0.826) (-1.531)					(-0.195) (-0.325)				
Δ_{-9}	-9 to -5	0.007	-0.006	0.396	-1.998	2.547	-0.051	-0.036	0.382	-2.234	1.032
		(0.248) (-0.421)					(-1.637) (-1.906)				
Δ_{-4}	-4 to -2	-0.111	-0.017	0.783	-9.824	1.175	-0.103	-0.032	0.608	-2.899	2.348
		(-2.044)* (-1.963)*					(-2.061)** (-1.490)				
Δ_{-1}	-1	-0.043	-0.028	1.698	-13.941	8.051	0.080	0.008	1.666	-5.643	6.709
		(-0.363) (-0.055)					(0.583) (0.454)				
Δ_0	0	0.614	0.551	1.708	-4.070	11.486	-0.024	0.041	2.105	-10.009	8.475
		(5.174)** (5.666)**					(-0.140) (0.314)				
Δ_1	1	-0.014	0.042	1.993	-18.588	6.751	0.545	0.149	1.626	-3.907	7.343
		(-0.100) (0.808)					(4.077)** (3.380)**				
Δ_2	2	-0.033	-0.052	0.993	-3.669	5.860	-0.056	-0.012	1.018	-4.419	3.069
		(-0.485) (-0.680)					(-0.666) (-0.641)				
Δ_3	3 to 5	-0.103	-0.055	0.440	-4.286	1.550	-0.035	-0.028	0.437	-1.321	1.892
		(-3.382)** (-3.922)**					(-0.985) (-1.614)				
Δ_6	6 to 10	-0.054	-0.048	0.197	-0.926	0.556	-0.053	-0.017	0.330	-2.466	0.912
		(-3.959)** (-3.950)**					(-1.969)* (-2.087)*				

Notes:
a. *The table shows summary statistics for the basic annual volatility (γ), the annualised daily time structure increment (η) and the announcement-induced changes in volatility. Good (bad) news announcements are those for which the reported eps exceeds (is less than) the mean forecast eps.*
b. *The Δ_λ represent the difference between normal volatility levels and volatility for the period/day beginning on day λ.*
c. *The statistics given beneath each mean are the t-statistic (left) and the Wilcoxon Z-statistic (right). The t-statistic equals the mean divided by its standard error. The Z-statistic is distributed as Normal (0, 1).*
d. ** = significant at 5%; ** = significant at 1% (two-tailed).*

Table 4 Regression results for equations (5a), (5b), (5c) and (5d)

	(5a)	(5b)	(5c)	(5d)
CONSTANT	0.841	0.713	0.983	0.942
	(2.399)**	(2.043)*	(2.721)**	(2.550)**
BAD	-0.670		-0.674	
	(-3.153)**		(-3.197)**	
HI		-0.556	-0.564	
		(-1.960)*	(-2.046)*	
BADHI				-1.393
				(-2.835)**
BADLO				-0.565
				(-2.766)**
GOODHI				-0.376
				(-1.154)
γ	-0.430	-0.209	-0.152	-0.157
	(-0.415)	(-0.202)	(-0.150)	(-0.156)
MV	-0.000	-0.000	-0.000	-0.000
	(-0.516)	(-1.288)	(-1.327)	(-1.364)
R squared	0.029	0.014	0.041	0.043
No. in sample	365	365	365	365

Notes: a. *The table gives the coefficients on the following equations*

$$\Delta_{0,k} = \mathrm{A} + \mathrm{B}BAD_k + \mathrm{G}\gamma_k + \mathrm{H}MV_k + \varepsilon_k \quad (5a)$$

$$\Delta_{0,k} = \mathrm{A} + \mathrm{C}HI_k + \mathrm{G}\gamma_k + \mathrm{H}MV_k + \varepsilon_k \quad (5b)$$

$$\Delta_{0,k} = \mathrm{A} + \mathrm{B}BAD_k + \mathrm{C}HI_k + \mathrm{G}\gamma_k + \mathrm{H}MV_k + \varepsilon_k \quad (5c)$$

$$\Delta_{0,k} = \mathrm{A} + \mathrm{D}BADHI_k + \mathrm{E}BADLO_k + \mathrm{F}GOODHI_k + \mathrm{G}\gamma_k + \mathrm{H}MV_k + \varepsilon_k \quad (5d)$$

$\Delta_{0,k}$ *is the difference between normal volatility levels and volatility at the end of the day of announcement k;*

BAD_k *takes the value 1 if the news is bad (actual eps lower than mean forecast);*

HI_k *takes the value 1 if the announcement has high SIGMAEPS;*

$BADHI_k$ *takes the value 1 if the news is bad and has high SIGMAEPS;*

$BADLO_k$ *takes the value 1 if the news is bad and has low SIGMAEPS;*

$GOOD_k$ *takes the value 1 if the news is good;*

γ *is the 'normal' volatility level; and*

MV is the market value of the firm 10 days before the announcement.

b. *t-statistics are given in parentheses. * = significant at 5%; ** = significant at 1%. (one-tailed)*

Table 5 Regression results for equations (6a), (6b), (6c) and (6d)

	(6a)	(6b)	(6c)	(6d)
CONSTANT	0.724	0.749	0.573	0.594
	(2.521)**	(2.733)**	(1.858)*	(1.858)*
BAD	0.383		0.392	
	(1.949)*		(1.993)*	
HI		0.569	0.578	
		(2.146)*	(2.164)*	
BADHI				1.044
				(2.178)*
BADLO				0.339
				(1.621)
GOODHI				0.490
				(1.582)
γ	-1.460	-1.729	-1.745	-1.745
	(-1.838)*	(-2.132)*	(-2.110)*	(-2.105)*
MV	-0.000	-0.000	-0.000	-0.000
	(-2.808)**	(-1.480)	(-1.429)	(-1.424)
$GOOD\Delta_0$	-1.238	-1.260	-1.231	-1.233
	(-9.606)**	(-10.024)**	(-9.398)**	(-9.428)**
$BAD\Delta_0$	-1.157	-1.138	-1.138	-1.134
	(-11.620)**	(-11.537)**	(-11.957)**	(-11.959)**
R squared	0.660	0.662	0.666	0.666
No. in sample	365	365	365	365

Notes: a. *The table gives the coefficients on the following equations:*

$$\delta_{1,k} = \mathrm{A} + \mathrm{B}BAD_k + \mathrm{G}\gamma_k + \mathrm{H}MV_k + \mathrm{I}GOOD\Delta_{0,k} + \mathrm{J}BAD\Delta_{0,k} + \varepsilon_k \quad (6a)$$

$$\delta_{1,k} = \mathrm{A} + \mathrm{C}HI_k + \mathrm{G}\gamma_k + \mathrm{H}MV_k + \mathrm{I}GOOD\Delta_{0,k} + \mathrm{J}BAD\Delta_{0,k} + \varepsilon_k \quad (6b)$$

$$\delta_{1,k} = \mathrm{A} + \mathrm{B}BAD_k + \mathrm{C}HI_k + \mathrm{G}\gamma_k + \mathrm{H}MV_k + \mathrm{I}GOOD\Delta_{0,k} + \mathrm{J}BAD\Delta_{0,k} + \varepsilon_k \quad (6c)$$

$$\delta_{1,k} = \mathrm{A} + \mathrm{D}BADHI_k + \mathrm{E}BADLO_k + \mathrm{F}GOODHI_k + \mathrm{G}\gamma_k + \mathrm{H}MV_k + \mathrm{I}GOOD\Delta_{0,k} + \mathrm{J}BAD\Delta_{0,k} + \varepsilon_k \quad (6d)$$

$\delta_{1,k}$ is the change in volatility between the end of day 0 and the end of day 1;
$GOOD\Delta_{0,k}$ and $BAD\Delta_{0,k}$ are the $\Delta_{0,k}$ for good news and bad news announcements, respectively; and other variables are defined in table 4.

b. *t-statistics are given in parentheses. * = significant at 5%; ** = significant at 1%. (one-tailed)*