Stock price reaction to profit warnings: The role of time-varying risk

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Abstract

This study investigates the role of time-varying betas, event-induced variance and conditional heteroskedasticity in the estimation of abnormal returns around important news announcements. Our analysis is based on the stock price reaction to profit warnings issued by a sample of firms listed on the Hong Kong Stock Exchange (HKEx). The standard event study methodology indicates the presence of price reversal patterns following both positive and negative warnings. However, incorporating time-varying betas, event-induced variance and conditional heteroskedasticity in the modelling process results in post-negative-warning price patterns that are consistent with the predictions of the efficient market hypothesis (EMH). These adjustments also cause the statistical significance of some post-positive-warning cumulative abnormal returns (CARs) to disappear and their magnitude to drop to an extent that minor transaction costs would eliminate the profitability of the contrarian strategy.

1. Introduction

This study investigates the market reaction to profit warnings[1] in the Hong Kong Stock Exchange (HKEx). Empirical evidence on the price reaction to profit warnings is limited to a few markets, such as the US, the UK and mainland China. Clare (2001) shows that investors in the UK tend to overreact more to negative warnings than to positive ones. Using Chinese data, Lui et al. (2009) find that stock prices overreact to the negative news contained in profit warnings. Specifically, they report a significant price drop of about -3% over the [-1, +1] window and a significant price increase of 7.81% over the [+2, +60] window around negative warnings. Consistent with the overreaction hypothesis, Tucker (2004) documents that investors react more negatively to firms that warn, when they anticipate negative earnings news, than those that do not warn. Jackson and Madura (2003) examine stock price behavior around profit warnings containing negative news in the US market. They find a significant price drop of -21.7% over the eleven-day period ending five days after the announcement. However, they find no evidence of reversal after this period and conclude that the market reaction to negative warnings is not excessive.

Previous studies on the stock price reaction to profit warnings are based on the standard event study methodology, which ignores the potential impact of news on stock betas and the residual variance (Brown et al. 1988; Corrado and Jordan 1997; Cyree and DeGennaro 2002; Lui et al. 2009; Savickas 2003; Zolotoy 2011; Cam and Ramiah 2014), a deficiency that may hinder the testing of the efficient market hypothesis (EMH).[2] Specifically, if a stock's beta changes after the event date, the use of the pre-event beta may result in inaccurate abnormal return estimates. Furthermore, several studies argue that ignoring the heteroskedastic nature of volatility and event-induced variance will lead to biased market model parameter estimates and inconsistent test statistics (e.g., Akgiray 1989; Corhay and Tourani-Rad 1994).

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[1] Profit warnings are announcements made by publicly traded companies, prior to the issuance of their formal financial reports, to warn investors that their earnings will differ from previously expected levels. Profit warnings can be either positive or negative.

[2] See Yen and Lee (2008) for a thorough review of the literature on efficiency market hypothesis.

It is widely documented in the literature that equity betas are not constant over time. For example, Klemkosky and Martin (1975) and Bollerslev et al. (1988) argue that investors' expected returns are conditional on the information available at any particular point in time and their consistent reestimation of factor returns causes the betas of risky assets to vary considerably over time. Consistent with this prediction, several studies find that estimated betas exhibit statistically significant time variation (see, e.g., Harvey 1989; Ferson and Korajczyk 1995; Faff et al. 2000). Many researchers also show that the variation in betas is more pronounced around important news announcements. Zolotoy (2011), for instance, argues that, as equity value tends to rise (fall) following the arrival of good (bad) news, the weight attached to debt falls (rises). As such, the release of positive (negative) news decreases (increases) the riskiness of equity investments. Similarly, Lui et al. (2009) find that the systematic risk of individual stocks reacts asymmetrically to the positive and negative news contained in the analyst reports. However, Brown et al. (1988) argue that, as surprises increase uncertainty, stock betas should increase following both favourable and unfavourable surprises. Specifically, they claim that investors tend to set prices before the full ramifications of a dramatic financial event become known, and the arrival of news immediately causes risk-averse investors to set stock prices significantly below their conditional expected values. Using a sample of the 200 largest S&P firms over the period 1962-1985, Brown et al. (1988) show that the variance of returns, the residual variance and the coefficient of systematic risk exhibit significant increases following daily residual returns in excess of 2.5 (sign ignored). Kalay and Lowenstein (1985) argue that, since events convey information to the market, stock price volatility should also increase in the post-announcement period. They also maintain that the incremental risk above that on a random day may not be fully diversifiable. Using a sample of 302 US firms for the period 1962-1980, they show that stock betas exhibit a significant increase in the aftermath of dividend announcements. More recently, Patton and Verardo (2012) propose a simple learning model, which suggest that investors use firm-specific news to extract information on the aggregate economy. They argue that since earnings are affected by both market-wide and firm-specific conditions, investors can use earnings of the announcing firms to revise their expectations about the profitability of other firms in the economy. This process of learning across stocks is expected to drive up the comovement between announcing stocks and other stocks and yield an increase in the market beta of the announcing stocks. Consistent with the predictions of the learning model, Patton and Verardo show that the betas of the constituents of the S&P 500 increase significantly around earnings announcements, regardless of whether the news is good or bad.

The extant literature has recognised the importance of adjusting for stochastic volatility around the event period. For example, Brown and Warner (1980) argue that the failure to adjust for the event-induced variance may result in biased estimates of the traditional test statistics, and that the power of these tests can be improved by appropriately modelling the volatility process. To control for the event-induced variance, Boehmer et al. (1991) propose a statistical test, generated by first standardising event-period returns by the estimation-period standard deviation and then dividing the cross-sectional mean of the standardised returns by their cross-sectional standard deviation. Savickas (2003) argues that a limitation of Boehmer et al.'s approach stems from the implicit assumption that the event-induced variance is the same across all sample stocks. Brockett et al. (1999) model the volatility process around the events using a market model with GARCH effects and time-varying betas. However, their approach ignores the importance of event-induced variance. Savickas (2003) addresses the conditional heteroskedastic behavior of volatility and the event-induced residual variance in a single model. Nevertheless, his model ignores the importance of time-varying betas, a phenomenon that may be particularly important around dramatic financial events (see, e.g., Brown et al. 1988; Zolotoy 2011; Lui et al. 2009).

In this study, we investigate the market reaction to profit warnings using an event study methodology that addresses the conditional heteroskedastic behavior of volatility, the time-varying betas and the event-induced variance simultaneously. Our contribution to the literature is twofold. First, we examine whether the nature of profit warnings affects a stock's beta. Brown et al. (1988) shows that stock betas increase following daily price shocks (daily residual returns) of ±2.5 percent or more. However, we argue that large daily price shocks may be caused by the behavior of noise traders rather than the arrival of news. Thus, using profit warnings as the events provides a cleaner test of the impact of the arrival of news on time-varying betas. Second, we propose an event study methodology that adjusts the abnormal return estimates and statistical tests for the time-varying betas and the event-induced residual variances as well as the conditionally heteroskedastic behavior of volatility. Specifically, we improve on Savickas' (2003) model by allowing the beta parameter of the market model to vary over time, while adjusting for the event-induced variance and conditional heteroskedasticity. We argue that this improvement is important not only because a stock beta varies systematically over time, but also because its variation is likely to be more pronounced around news events (Brown et al., 1988; Zolotoy, 2011; Lui et al., 2009).

The results of our study can be summarised briefly as follows. Firstly, we observe the highest positive (negative) abnormal returns on the day on which positive (negative)

warnings are released. We also report strong price reversal patterns following both positive and negative warnings. Secondly, consistent with Brown et al.'s (1988) view that surprises increase uncertainty, the average beta of event stocks increases significantly after both positive and negative warnings. Thirdly, we show that the statistical significance of the cumulative abnormal returns (CARs) following negative warning announcements disappears completely after we account for the time-varying betas. We also find that the time-varying beta adjustments reduce the magnitude and the statistical significance of the price reversal patterns following positive warnings. Fourthly, the average abnormal returns on the first two days following warnings containing positive news lose their significance after the event-induced variance and conditional heteroskedasticity are accounted for, while the subsequent CARs become much smaller. Finally, we show that adjusting for time-varying betas, event-induced variance and conditional heteroskedasticity simultaneously yields even smaller post-positive-warning CARs. We argue that, although many of the post-positive-warning CARs remain significant after the incorporation of time-varying betas, event-induced variance and conditional heteroskedasticity in the modelling process, these patterns should not be used as evidence against the EMH for at least three reasons. First, the results from the pooled ordinary least square (OLS) regressions indicate that the post-positive-warning CARs are not related to the abnormal returns on the announcement days. This finding is not consistent with the prediction of the overreaction hypothesis, which suggests that greater overreaction would lead to greater correction (see, e.g., Cox and Peterson 1994; Choi and Jayaraman 2009). Second, the magnitude and the statistical significance of the post-positive-warning CARs are highly sensitive to the way in which abnormal returns are measured. Finally, incorporating time-varying betas, event-induced variance and conditional heteroskedasticity into the modelling process yields post-positive-warning CARs that are too small to cover the transaction costs that one would incur in pursuing a contrarian strategy.

The remainder of the paper is organised as follows. Section 2 describes the dataset. Section 3 presents the empirical tests and results. Section 4 provides some additional results and robustness checks, and Section 5 concludes.

2. Data

The statements of profit warnings used in this study are obtained from the HKEx website. The exchange began publishing these statements in July 2007. Our initial sample includes all such statements issued during the period from July 2007 to July 2012. Daily closing prices of the issuing firms and the Hang Seng index are obtained from DataStream. Our final sample

constitutes a total of 1,723 profit warnings, of which 1,238 contain negative news and 485 contain positive news about firms' earnings prospects. The dominance of warnings containing negative news in our sample may be attributed to the fact that only bad news is emphasised in the "listing rules" in Hong Kong (see, e.g., Wang and Zhang 2011). Furthermore, several studies suggest that warnings are more likely to be issued prior to negative than positive news (see, e.g., Barmber and Cheon 1998; Libby and Tan 1999; Wang and Zhang 2011).

3. Tests and results

To estimate the abnormal returns around profit warnings, we initially use the standard event study methodology. Then, we relax the market model assumption that stock betas and residual variance are constant over time and not affected by the arrival of news. Specifically, we use a bivariate form of Engle and Kroner's (1995) BEKK GARCH model to account for time-varying betas. Then, we employ a model developed by Savickas (2003) to control for the effect of event-induced variance and the heteroskedastic behavior of volatility on the abnormal return estimates. Finally, we improve on Savickas' approach by allowing stock betas to vary over time.

3.1. Standard event study

The approach most commonly used to estimate expected returns is the market model:[3]

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}, \ E(\varepsilon_{it}) = 0, var(\varepsilon_{it}) = \sigma_i^2 , \tag{1}$$

where $R_{i,t}$ and $R_{m,t}$ are day t's continuously compounded returns of stock i and the market portfolio m, respectively; α_i and β_i are the parameters of the market model and ε_{it} is the error term, which is assumed to have a zero mean and a constant variance, σ_i^2. Eq.(1) is estimated over the [-200, -15] window prior to profit warnings. The abnormal return of stock i on day t, or $AR_{i,t}$, is then estimated as

$$AR_{it} = R_{it} - (\widehat{\alpha_i} + \widehat{\beta_i} R_{mt}). \tag{2}$$

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[3] Dyckman et al. (1984) show that the market model performs significantly better than other models, such as the index or average return models. Similarly, Armitage (1995: 25) argues that "…the market model is most commonly used to generate expected returns and no better alternative has yet been found despite the weak relationship between beta and actual returns…".

The price effect of profit warnings is measured using the daily average abnormal return ($\overline{AR_t}$) and the cumulative average abnormal return ($\overline{CAR_s}$). The average abnormal return on day t is computed as

$$\overline{AR_t} = \frac{\sum_{i=1}^{N} AR_{i,t}}{N}. \tag{3}$$

The cumulative abnormal return of stock i over a window of S days starting one day after the event is given as

$$CAR_{is} = \sum_{t=1}^{S} AR_{it}. \tag{4}$$

The average cumulative abnormal return over a window of S days beginning one day after the event and across N stocks, is computed as

$$\overline{CAR_s} = \frac{1}{N}\sum_{i=1}^{N} CAR_{is}. \tag{5}$$

Two test statistics, T_1 and T_2, are used to assess the statistical significance of $\overline{AR_t}$ and $\overline{CAR_s}$, respectively, and are specified as follows:

$$T_1 = \frac{\overline{AR_t}}{\widehat{\sigma_{AR}}/\sqrt{N}} \text{ and } T_2 = \frac{\overline{CAR_s}}{\widehat{\sigma_{CAR}}/\sqrt{N}}, \tag{6}$$

where $\widehat{\sigma_{AR}}$ and $\widehat{\sigma_{CAR}}$ are the standard deviations of $AR_{i,t}$ and $CAR_{i,s}$, respectively, and are estimated as

$$\widehat{\sigma_{AR}} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(AR_{i,t} - \overline{AR_t})^2} \text{ and } \widehat{\sigma_{CAR}} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(CAR_{i,s} - \overline{CAR_s})^2}.$$

When standard assumptions hold, T_1 and T_2 follow Student t-distributions with $N-1$ degrees of freedom.[4]

Table 1 reports the average daily ARs and the CARs around profit warnings. Panel A reports the CARs following negative warnings. The average AR on the announcement date is

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[4] For robustness purposes, we also use Newey-West heteroskedasticity, the serial correlation consistent estimator and the J-statistic of Campbell et al. (1997) and our conclusions remain unchanged. Details of these results are available upon request.

-3.46% and is highly significant (with a t-value of -16.73). The average CARs following the announcements of bad news are positive and significant, except for on day 1, with values increasing monotonically from 0.01% on day 1 to 1.25% for the [+1, +10] window. This finding indicates that, on average, an investor can earn a significant abnormal return of 1.25% by holding a stock for a period of ten days starting one day after a negative warning.

Insert Table 1 about here

Panel B presents the results on the price reaction to positive warnings. The average AR on the announcement date is positive (with a value of 3.9%) and is statistically significant at less than the 1% level. The average CARs following positive news are negative and highly significant, indicating strong price reversal following the arrival of good news. This finding suggests that, on average, an abnormal return of 2.82% can be earned by short selling a stock one day after a positive warning and repurchasing it ten days later. Our evidence is similar to that of Lui et al. (2009), who find strong share price reversal following negative warnings in the Chinese main market. Price reversal patterns are also documented by several studies on the price reaction to shocks. For instance, Atkins and Dyl (1990) report significantly negative (positive) average CARs from following the three largest winners (losers) on 500 randomly selected trading days from 1975 to 1984. Bremer and Sweeney (1991) examine stock price behavior following a one-day price change of -10% or less, and their results confirm the overreaction hypothesis.

We argue that one weakness of the existing literature on the stock price reaction to profit warnings stems from the explicit assumption that the stock beta is constant over time and is not affected by the arrival of news. In this study, we adopt the bivariate form of Engle and Kroner's (1995) BEKK GARCH model to estimate time-varying systematic risk and the conditional abnormal returns.

3.2. *Time-varying betas*

Following Tsui and Yu (1999), Choudhry (2005) and Choudhry et al. (2010), we use the bivariate form of Engle and Kroner's (1995) BEKK GARCH to estimate the conditional betas of the market model. Under this model, the conditional variance-covariance matrix is specified as follows:

$$y_t = v + \Xi_t; \; \Xi_t \big|\Psi_{t-1} \sim N(0, H_t), \qquad (7)$$

$$H_t = C'C + A'\Xi_{t-1}\Xi'_{t-1}A + B'H_{t-1}B, \qquad (8)$$

where $y_t = (R_{it}, R_{m,t})$ is a 2 x 1 vector containing the continuously compounded returns of stock i and the market portfolio m; v is a 2 x 1 vector of constants; H_t is a 2 x 2 conditional variance-covariance matrix, which depends on the elements of the information set Ψ_{t-1} of the past value of the error term Ξ_t; C, A and B are 2 x 2 matrices of parameters.

Engle and Kroner (1995) argue that the BEKK model is sufficiently general as it includes all positive definite diagonal representations and nearly all positive definite vector representations. It has also been suggested that the BEKK model addresses an important weakness of the general specification of the multivariate GARCH by ensuring that the H_t matrix is always positive definite (see, e.g., Bollerslev et al. 1994).

Eqs.(7) and (8) are estimated separately for the [-201, -1] and [0, +200] windows around warning dates, and the time-varying beta of stock i ($\beta_{i,t}$) is computed as

$$\widetilde{\beta_{it}} = \frac{h_{12,t}}{h_{22,t}}, \qquad (9)$$

where $h_{12,t}$ and $h_{22,t}$ are elements of the matrix H_t and are defined as the conditional covariance between stock i's returns and the market portfolio returns, and the conditional variance of the market portfolio returns, respectively.

The standard paired t-test and the non-parametric Wilcoxon signed rank test (WSRT) are used to judge whether the average pre-warning beta, measured over the [-201, -1] window prior to the announcement date, is significantly different from the average post-warning beta, measured over a window of S days beginning one day after the event.

To account for the potential effect of changes in beta on the abnormal returns around profit warnings, we estimate conditional beta-adjusted abnormal returns as follows:

$$AR_{it} = R_{it} - (\widetilde{\alpha_i} + \widetilde{\beta_{it}}\, R_{mt}). \qquad (10)[5]$$

The average conditional beta-adjusted average ARs and CARs are calculated using Eqs.(2) and (5), respectively. The standard t-test is also used to gauge their statistical significance.

Table 2 reports the changes in conditional betas following profit warnings. Panel A presents the changes in conditional betas following negative warnings. The mean (median) pre-warning conditional beta is 0.609 (0.579). The results suggest that the post-warning betas

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[5] The parameter α_i is generated by regressing the variable $(R_{i,t} - \beta_{i,t}\, R_{m,t})$ against a constant term.

are higher than the pre-warning betas, across all post-event windows. Both the paired t-test and the WSRT suggest that the difference between the pre- and post-warning betas is statistically significant. Panel B presents the conditional betas around positive warnings. The mean (median) conditional beta over the [-201, -1] window prior to warnings containing positive news is 0.679 (0.685). Both the paired t-test and the WSRT indicate that stock betas increase significantly following the arrival of positive news.

Insert Table 2 about here

Figures 1 and 2 indicate the presence of a structural break in average daily betas following both positive and negative warning announcements. Specifically, the figures show that betas are relatively stable before warning announcements, increase substantially on the announcement dates and stabilise thereafter. In contrast to Patton and Verardo (2012), our results suggest that betas do not revert back to the pre-announcement average over the ten-day window following warning announcements.

Insert Figures 1 & 2 about here

We conduct two additional tests to investigate whether the changes in betas are indeed caused by the arrival of news. First, for each event stock, we select a date randomly from its pre-warning window. We treat the randomly selected dates as if they were the event dates. The paired t-test and WSRT suggest that the changes in beta following these pretended event dates are not significantly different from zero (the table is omitted to conserve space). Second, we match event stock with another stock from the same industry, with the closest market capitalization and with no price sensitive news within the [-10, +10] window around the warning announcement dates. In untabulated results, we find that the changes in the betas of the control stocks around the warning events are not significantly different from zero, implying that the increase in the post-warning betas is more likely to be caused by the arrival of news than the systematic time-varying nature of stock betas. This evidence is consistent with Kalay and Lowenstein (1985), Brown et al. (1988) and Patton and Verardo (2012), who show that, as surprises increase uncertainty, systematic risk increases significantly in the aftermath of both positive and negative news. Hence, ignoring the time-varying nature of the betas may result in biased abnormal return estimates.

Table 3 reports the conditional beta-adjusted average ARs and conditional beta-adjusted average CARs following the release of profit warnings. Panel A focuses on the negative warnings. Our results indicate that the post-warning CARs carry a positive sign.

However, none of these post-warning CARs is significantly different from zero. This evidence indicates that individual stocks in Hong Kong react efficiently to the negative news contained in profit warnings. Both the paired t-test and WSRT suggest that the values of time-varying-beta-adjusted CARs are significantly smaller than their corresponding market model CARs in Table 1. Panel B also presents the conditional beta-adjusted average ARs and CARs following positive warnings. Stock prices respond positively to the arrival of good news. The average conditional beta-adjusted abnormal return on the announcement date is 4.11%. This figure is statistically significant at less than the 1% level. All post-warning conditional beta-adjusted CARs are significantly negative, ranging from CAR_1 = -0.67% to CAR_9 = -1.27%. Both the standard t-test and the WSRT indicate a significant decline in the values of post-positive-warning CARs following time-varying beta adjustment.

Insert Table 3 about here

In short, the findings in this section suggest that the price reversal patterns following negative profit warnings are more likely to be the outcome of model misspecification than investors' overreaction. However, while the negative CARs following positive warnings become small in magnitude, they remain highly significant even after the systematic variations in stock betas are accounted for.

3.3. *Conditional heteroskedasticity and event-induced variance*

As discussed earlier, the extant literature suggests that accounting for the conditionally heteroskedastic behavior of volatility and event-induced variance improves the market model parameter estimates and the power of the statistical tests. Following Savickas (2003), we estimate the abnormal returns as follows:

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\begin{cases}
R_{it} = \alpha_i + \beta_i R_{mt} + \gamma_{in} D_{in} + \varepsilon_{it}; \ \varepsilon_{it} \big| \Omega_{it-1} \sim N(0, h_{it}^2) & (11) \\
h_{it}^2 = \varphi_i + \psi_i h_{it-1}^2 + \theta_i \varepsilon_{it-1}^2 + \phi_{in} D_{in} & (12)
\end{cases}
$$

where ε_{it} in Eq.(11) is a residual term, with mean of zero and time-varying variance h_{it}^2 assumed to follow a GARCH (1,1) process[6]. The subscript $n \in [1, +N]$ of the variable D_{in} denotes the number of days after the event day t. $D_{i1}, D_{i2}, ..., D_{iN}$ are dummy variables with a value of unity if $t \in [0, +1], t \in [0, +2], ..., t \in [0, +N]$, respectively, and zero otherwise.

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[6] The results from GJR-GARCH (1,1) and E-GARCH (1,1) are very similar to those reported here. Further details are available upon request.

β_{in} is the change in the systematic risk measured over the window of length n after the profit warning. The rest of the variables are as defined previously. The parameter γ_{in} in Eq.(11) reflects the abnormal returns around the event and the parameter ϕ_{in} in Eq.(12) captures the event-induced residual variance.

Savickas (2003) argues that the increase in variance around events may result in the misspecification of the traditional test statistics, and proposes the following test to account for the stochastic behavior of volatility during both event and non-event periods:

$$test = \sum_{i=1}^{N} \frac{S_{it}}{N} / \sqrt{\frac{1}{N(N-1)} \sum_{i=1}^{N} \left(S_{i,t} - \sum_{j=1}^{N} S_{j,t}/N\right)^2} \tag{13}$$

where

$$S_{it} = \frac{\widehat{\gamma_{in}}}{\sqrt{\widehat{h_{in}^2}}}$$

where $\widehat{\gamma_{in}}$ is the estimated mean abnormal return of security i on a given day or window and $\widehat{h_{in}^2}$ is the estimated standard deviation of the abnormal return on a given day (we use the average of $\widehat{h_{it}^2}$ when abnormal returns are estimated over a window). The test statistic presented in Eq.(13) follows the Student t-distribution with $N - 1$ degrees of freedom. Savickas argues that his test has more power as it allows the event-induced volatility effect to differ across securities and each security's variance to be stochastic outside the event period.

Table 4 presents the abnormal return estimates obtained using Savickas' (2003) approach. Panel A shows that the abnormal returns following negative warnings are small and not significantly different from zero. The paired t-test suggests that, except on day 1, the CARs from Savickas' model are significantly smaller than the CARs obtained using the standard event methodology approach (see Panel A of Table 1). The WSRT also indicates that the difference between the ARs and CARs from Savickas' approach and the market model are significant for days 0 and +1 and for the window [+1, +9] after the negative warning. The ARs and CARs reported in Panel A are also smaller than their time-varying-beta-adjusted counterparts (see Panel A of Table 3). Overall, the results in Panel A are consistent with the predictions of the EMH, which posits that stock prices adjust instantly and accurately to the arrival of news.

Insert Table 4 about here

Panel B of Table 4 shows that the average ARs and CARs from Savickas' model, following positive warnings, are negative but much smaller than those from the standard

market model (Panel B of Table 1) and from the market model with time-varying beta (Panel B of Table 3). The AR_1 and CAR_2 after warnings containing positive news are not significantly different from zero. The subsequent CARs are significantly negative, but small in magnitude, ranging from -0.27% (CAR_3) to -0.14% (CAR_7). While the abnormal returns immediately after the events are not significant, the results suggest that, on average, short selling a stock immediately after a positive news announcement and repurchasing it ten days later would generate a return of 0.17%. However, the average (median) relative bid-ask spread associated with our sample stocks during the study period is 3.06% (1.92%). Thus, such price patterns may not yield profits in excess of transaction costs and therefore cannot be used as evidence against the EMH.

3.4. *Conditional heteroskedasticity, event-induced variance and time-varying betas*

Savickas (2003) explicitly assumes that stock betas are constant over time and not affected by the arrival of news. To address this potential limitation, we replace the constant β_i parameter in Eq.(11) with the time-varying betas generated by the BEKK GARCH model. We argue that allowing betas to be stochastic both within and outside of the event period should yield more accurate estimates of the abnormal return and residual variance and should, therefore, improve the power and accuracy of the cross-sectional test statistic presented in Eq.(13).

The results of this analysis are reported in Table 5. Panel A shows that the average ARs and CARs following negative warnings are positive but not statistically significant (except for CAR_6). The paired t-test and the non-parametric WSRT indicate that the ARs and CARs in Panel A of Table 5 are in many cases significantly smaller in magnitude than their market model counterparts (Panel A of Table 1). Panel B of Table 5 shows that the ARs and CARs following positive warnings are small, but remain negatively significant. The paired t-test and the WSRT also suggest that the ARs and CARs in Panel B of Table 5 are significantly smaller than those generated by the standard market model. Furthermore, the ARs and CARs in Panel B of Table 5 are very similar in magnitude to those obtained using Savickas' model (Panel B of Table 4), implying that profits in excess of transaction costs cannot be earned from the contrarian strategy.

Insert Table 5 about here

In summary, the market model CARs suggest that investors overreact to both positive and negative warnings. However, adjusting for the time-varying risk and the event-induced variance causes the overreaction patterns following negative news to disappear completely.

These adjustments also cause abnormal returns on days +1 and +2 after positive warnings to lose their statistical significant (see Section 3.3) and the magnitudes of the remaining post-positive-warning CARs to decline to such an extent that a contrarian strategy does not earn a profit in excess of transaction costs. These findings are consistent with the large body of literature that posits that ignoring time-varying betas, the conditional heteroskedastic behavior of the residual variance, and the event-induced volatility may yield biased market model parameter estimates and inconsistent test statistics (e.g., Corhay and Tourani-Rad 1994; Brown et al. 1988; Savickas 2003; Kolari and Pynnönen 2010).

3.5. Multivariate analysis

So far, we have shown that incorporating the time-varying betas, event-induced variance and conditional heteroskedasticity into the modelling process causes the overreaction patterns after negative warnings to disappear completely. These adjustments also yield smaller, and in some cases statistically insignificant, post-positive-warning CARs. However, the presence of some significantly negative, albeit small, post-positive-warning CARs may still be used as an argument for the overreaction hypothesis. To verify the validity of this claim, we estimate the following pooled OLS regression:

$$CAR_{is} = \alpha_0 + \alpha_1 AR_{0i} + \sum_k \alpha_{ik} Control_i^k + IndustryDummies + YearDummies + \varepsilon,$$

(14)

where CAR_{is} is firm i's average cumulative abnormal return over a window of S days beginning one day after a positive warning; AR_{0i} is firm i's average event-day abnormal return (both AR_{0i} and CAR_{is} are adjusted for the time-varying betas, event-adjusted variance and conditional heteroskedasticity); $Control_i^k$ is a vector of control variables, which includes a set of firm-specific variables that are deemed to influence stock returns. These variables include the book-to-market ratio ($BTMV_i$), the natural logarithm of stock i's market capitalization measure ($lnMV_i$) and the average turnover – i.e., the daily trading volume divided by the number of shares outstanding ($AvgTO_i$). $BTMV_i$ and $lnMV_i$ are measured 11 days prior to the positive warning, while $AvgTO_i$ is computed over the [-105, -6] window prior to the positive warning. Industry and year dummies are included to control for the industry and year fixed effects. We also correct standard errors for firm-level clustering.

If the overreaction hypothesis holds, the parameter α_1 in Eq.(14) will be negative and significant, as the greater overreaction would lead to a greater correction (see, e.g., Cox and

Peterson, 1994; Choi and Jayaraman, 2009). Fama and French (1993, 1996) show that $BTMV_i$ and $lnMV_i$ are amongst the key determinants of cross-sectional stock returns. If smaller stocks reverse more than larger stocks, $\propto_2$ is expected to be negative and significant (see, e.g., Bremer and Sweeney 1991). The parameter $\propto_3$ is expected to be positive, as investors may overreact to a greater extent when positive warnings are made by mature firms than when they are made by growth firms[7]. Finally, if the price reversal process is caused by illiquidity, $\propto_4$ is expected to be negative and significant (see, e.g., Choi and Jayaraman 2009).

Insert Table 6 about here

The results of the pooled OLS estimates are shown in Table 6. The coefficient α_1 is negative for all post-event CARs, but only significant in the case of CAR3. This evidence contradicts the predictions of the overreaction hypothesis, which suggests that greater overreaction causes greater correction. The results indicate that the post-positive-warning price patterns are unlikely to be driven by the size effect, as the coefficient $\propto_2$ carries a positive, rather than the predicted negative, sign for all post-event CARs except for AR1 (significant at the 5% level) and CAR4 (statistically insignificant). The coefficient $\propto_3$ is generally negative, but only significant in the case of CAR4, which is too far from the event date. This finding suggests that growth opportunities do not play a major role in determining the post-positive-warning price reversal patterns. Finally, $\propto_4$ is negative, but not statistically significant, indicating that the post-positive-warning price patterns cannot be attributed to the illiquidity effect.

4. Robustness checks

4.1. *Alternative estimations of time-varying betas*

While the BEKK model has been widely used to estimate the conditional betas of the market model (Tsui and Yu 1999; Choudhry 2005; Choudhry et al. 2010), a number of other techniques have emerged for modelling and estimating time-varying betas[8]. For robustness purposes, we also estimate conditional betas using other popular members of the multivariate

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[7] The earnings of mature firms tend to be more stable and predictable than those of growth firms. Therefore, investors' surprise is likely to be greater when warnings are issued by mature firms.

[8] See, for example, Faff et al. (2000) for a detailed review of these techniques.

GARCH (M-GARCH) model family. Following Faff et al. (2000), we estimate a time series of conditional betas, β_{it}^G, for a stock i as

$$\beta_{it}^G = \frac{\rho_{im}\sigma_{it}}{\sigma_{mt}} \tag{15}$$

where σ_{it} and σ_{mt} are the time-varying conditional variances for the stock and the market, respectively, and ρ_{im} is the covariance between the stock and the market returns, which is assumed constant to overcome the onerous computational burden (see, e.g., Pagan, 1996). The time-varying conditional variances (σ_{it} and σ_{mt}) are initially modelled using the standard GARCH (1,1) specification. Then, the Exponential GARCH (EGARCH) of Nelson (1991) and the Threshold GARCH (TGARCH) of Glosten et al. (1993) are employed to model the asymmetry in the stock price volatility reaction to positive and negative shocks. Following Faff et al. (2000), we also use the in-sample mean squared error of forecasts, or $MSE_i = \sum (R_{it}^* - R_{it})^2 / T$, to assess the accuracy of each forecasted beta series (including those obtained using the BEKK model). Here, R_{it}^* are the predicted values of stock i's return series generated from the single index model with time-varying betas generated from Eq.(15), and T is the number of days in the estimation period.

The GARCH-, TGARCH- and EGARCH-based time-varying beta estimates are provided in Panel A of Table 7. The time-varying betas from the standard GARCH model are similar to those obtained from the BEKK model (see Table 2). Specifically, the GARCH model indicates that stock betas increase in the aftermath of news, but the increase is more pronounced following good than bad news. The TGARCH estimates suggest that stock betas increase significantly after positive warnings, but exhibit no significant changes following warnings containing negative news. The EGARCH model suggests that stock betas do not exhibit any significant changes in the post-warning periods, irrespective of the news contained in the warnings. Panel A of Table 7 also reports the average mean squared errors (MSEs) associated with the different conditional beta estimates. It shows that the post-negative-warning (post-positive-warning) average MSEs associated with the GARCH- and TGARCH-based estimates are 12.54x10⁻⁴ and 12.53x10⁻⁴ (23.93x10⁻⁴ and 23.94x10⁻⁴), respectively. However, the EGARCH estimates generate average MSEs of 50.10x10⁻⁴ and 50.47x10⁻⁴ for the cases of negative and positive warnings, respectively. This evidence suggests that GARCH and TGARCH estimates provide relatively more accurate forecasts of

time-varying betas than EGARCH[9]. It also implies that stock betas are more likely to exhibit significant increases after good news than bad news.

Insert Table 7 about here

To gain further insight into whether the price patterns following warnings depend on the way the conditional betas are estimated, we reestimate the ARs and CARs reported in Table 3 using the procedure described in Section 3.2, but with time-varying betas generated using the GARCH, TGARCH and EGARCH models, respectively. The results in Panel B of Table 7 indicate that, despite some variations in the magnitude and the statistical significance of the post-warning CARs, the general price patterns do not seem to depend on how the conditional betas are estimated and are consistent with those outlined earlier (see Section 3.2). Specifically, Panel B of Table 7 shows that the price reversal patterns following negative profit warnings disappear (almost) completely when the betas are allowed to vary over time. It also shows that, while the CARs following warnings containing good news remain significantly negative, their values decline considerably once adjusted for the time-varying betas[10].

4.2. *Subperiod analysis*

Many studies suggest that the stock market is becoming more efficient over time (e.g., Sullivan et al., 1999) suggesting that the post-warning price patterns may also vary over time. To test this prediction, we subdivide the sample into two subperiods: July 2007 to July 2009 and August 2009 to July 2012[11]. Table 8 presents the ARs and CARs from the standard market model (Section 3.1), the market model with time-varying betas (Section 3.2), the Savikas model (Section 3.3) and the Savikas model with time-varying betas (Section 3.4). Panel A of Table 8 presents the post-negative-warning and post-positive-warning ARs and CARs for the period from July 2007 to July 2009. The market model produces price patterns that are consistent with the predictions of the overreaction hypothesis. Specifically, the market model CARs following negative shocks are positive and significant, with an average

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[9] The average MSEs from the BEKK model are 12.58×10^{-4} and 24.06×10^{-4} for the negative and positive warnings, respectively. These figures are very close to those produced by the GARCH and TGARCH methods, but deviate considerably from those generated by EGARCH.

[10] Note that we also repeat the analysis in Section 4.4 using time-varying beta estimates from GARCH, TGARCH and EGARCH and our conclusions remain largely unchanged. Further details are available upon request.

[11] Subdividing the sample into three and four subperiods does not alter our main conclusions and the results are available upon request.

CAR of 2.4% to be earned over the ten-day window following a negative warning. Similarly, the post-positive-warning CARs are significantly negative, with a contrarian strategy earning an average CAR of -4.1% over the ten-day window after the announcement date. However, alternative abnormal return estimation methods imply that the post-warning price patterns are likely to be due to a bad model problem. Specifically, adjusting for the time-varying betas causes the post-negative-warning price patterns to disappear completely and the magnitude of the post-positive-warning CARs to decline considerably. The post-warning CARs become even smaller after the stochastic behavior of volatility during both event and non-event periods have been accounted for. In particular, CARs from Savickas' (2003) model are not significantly different from zero following warnings containing bad news, and are very small, and in many cases insignificant, after warnings containing good news. The simultaneous adjustment for the time-varying beta, event-induced variance and conditional heteroskedasticity yields slightly smaller CARs than the Savickas model.

Insert Table 8 about here

The post-negative-warning and post-positive-warning ARs and CARs for the period from August 2009 to July 2012 are presented in Panel B of Table 8. The results indicate that the price patterns following warnings with bad news are consistent with the EMH, irrespective of the abnormal return estimates. However, the post-positive-warning CARs seem to depend largely on the estimation method. The market model CARs suggest that investors overreact to warnings containing good news. Specifically, the post-positive-warning market model CARs are significantly negative and increase monotonically from CAR_1 = -0.7% to CAR_{10} = -2.3%. The market model with time-varying betas generates similar results, but with slightly smaller post-positive-warning CARs (CAR_1 = -0.6% and CAR_{10} = -1.7%). The Savickas (2003) approach breaks the monotonic abnormal return patterns, causing a large decline in the magnitude and the disappearance of the statistical significance of some of the post-positive-warning CARs. Similar results are obtained when the beta parameter in the Savickas model is allowed to vary systematically over time. Specifically, on average, shorting a stock one day after a positive warning and repurchasing it ten days later would only yield an abnormal profit of 0.1%. This figure is considerably smaller than the average (median) relative bid-ask spread of 2.75% (1.71%) associated with the sample stocks during

this period, implying that the contrarian strategy is not profitable after accounting for transaction costs[12].

5. Conclusion

This study examines the impact of announcements containing profit warnings on the risk and return characteristics of the underlying stocks. Our main purpose is to test whether the price reaction anomalies around profit warnings survive adjustments for the time-varying beta, event-induced variance and conditional heteroskedasticity. The standard event study methodology indicates the presence of strong price reversal patterns following both positive and negative warnings. Specifically, the abnormal returns are positive (negative) on the days on which positive (negative) warnings are released and negative (positive) on the subsequent days. These results are consistent with the findings of Lui et al. (2009), Bremer and Sweeney (1991) and Atkins and Dyl (1990).

Several studies show that the betas and residual variances of individual stocks are affected by the arrival of news (e.g., Brown et al. 1988; Grullon et al. 2005; DeAngelo et al. 2006). Others find that the residual variance of the standard market model varies systematically over time (see, e.g., Patell and Wolfson 1979; Kalay and Lowenstein 1985; Kolari and Pynnönen 2010). This study shows that relaxing these assumptions results in post-warning abnormal returns patterns that are largely consistent with the predictions of the EMH.

In conclusion, the results of this study suggest that, while the literature seems to produce several price anomalies, the efficient market hypothesis should only be rejected if the abnormal returns estimates survive stringent tests. Our conclusion is consistent with Park (1995), who finds that the overreaction to large price change disappears after bid-ask spread bounces are accounted for, and Fama (1998), who finds that most of the return anomalies around corporate announcement events are mitigated with reasonable changes to the way abnormal returns are measured.

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[12] We also stratify our sample stocks into different size and industry subsamples and our results remain unchanged. Specifically, we show that the magnitude and statistical significance of CARs are highly sensitive to the estimation method. While the standard market model results are in many cases consistent with the predictions of the overreaction hypotheses, the price patterns obtained after accounting for the time-varying betas, event-induced variance and conditional heteroskedasticity are generally consistent with the predictions of the EMH. Further details of these results are available upon request.

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Table 1 Price reaction to profit warnings: Standard event study approach

	Panel A: Negative warnings		Panel B: Positive warnings	
	Value (%)	t-statistic	Value (%)	t-statistic
$\overline{AR}_0$	-3.46***	-16.73	4.16***	12.46
$\overline{AR}_1$	-0.01	0.04	-0.90***	-5.00
$\overline{CAR}_{[1,2]}$	0.41*	1.76	-1.27***	-4.68
$\overline{CAR}_{[1,3]}$	0.49*	1.89	-1.30***	-4.31
$\overline{CAR}_{[1,4]}$	0.55*	1.87	-1.43***	-4.30
$\overline{CAR}_{[1,5]}$	0.74**	2.22	-1.73***	-4.89
$\overline{CAR}_{[1,6]}$	0.90**	2.45	-1.98***	-5.04
$\overline{CAR}_{[1,7]}$	1.02***	2.58	-2.15***	-5.10
$\overline{CAR}_{[1,8]}$	1.09***	2.66	-2.40***	-5.51
$\overline{CAR}_{[1,9]}$	1.28***	2.97	-2.71***	-5.99
$\overline{CAR}_{[1,10]}$	1.25***	2.73	-2.82***	-5.87
N	1238		485	

The abnormal return of stock i on day t, or $AR_{i,t}$, is estimated using the parameters of the standard market model over the [-200, -15] window prior to profit warnings. The price effect of profit warnings is measured using the daily average abnormal return ($\overline{AR}_t$) and the cumulative average abnormal return ($\overline{CAR}_s$). The average abnormal return on day t is given by $\overline{AR}_t = \frac{\sum_{i=1}^{N} AR_{i,t}}{N}$.

The cumulative abnormal return of stock i over a window of S days starting one day after the event is given by $CAR_{i,s} = \sum_{t=1}^{S} AR_{i,t}$.

The average cumulative abnormal return over a window of S days beginning one day after the shock and across N stocks is given by $\overline{CAR}_s = \frac{1}{N} \sum_{i=1}^{N} CAR_{i,s}$.

A standard t-test is used to check the statistical significance of $\overline{AR}_t$ and $\overline{CAR}_s$.

***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Table 2 Conditional betas following profit warnings

	Mean	t-statistic	Median	t-statistic
Panel A: Conditional betas around negative warnings				
$\beta_{[-201,-1]}$	0.609		0.579	
$\beta_{[0,+1]}$	0.655***	4.14	0.625***	4.30
$\beta_{[0,+2]}$	0.654***	3.98	0.623***	4.14
$\beta_{[0,+3]}$	0.653***	3.88	0.623***	4.17
$\beta_{[0,+4]}$	0.652***	3.61	0.622***	4.12
$\beta_{[0,+5]}$	0.652***	3.69	0.622***	4.12
$\beta_{[0,+6]}$	0.652***	3.74	0.619***	4.08
$\beta_{[0,+7]}$	0.652***	3.78	0.619***	4.08
$\beta_{[0,+8]}$	0.653***	3.82	0.619***	4.08
$\beta_{[0,+9]}$	0.653***	3.89	0.619***	4.10
$\beta_{[0,+10]}$	0.654***	3.93	0.617***	4.11
N		1238		
Panel B: Conditional betas around positive warnings				
	Mean	t-statistic	Median	t-statistic
$\beta_{[-201,-1]}$	0.679		0.685	
$\beta_{[0,+1]}$	0.729***	2.93	0.707***	2.96
$\beta_{[0,+2]}$	0.726***	2.76	0.707***	2.86
$\beta_{[0,+3]}$	0.727***	2.78	0.709***	2.86
$\beta_{[0,+4]}$	0.728***	2.88	0.709***	2.93
$\beta_{[0,+5]}$	0.728***	2.89	0.709***	2.90
$\beta_{[0,+6]}$	0.728***	2.88	0.711***	2.88
$\beta_{[0,+7]}$	0.728***	2.90	0.711***	2.90
$\beta_{[0,+8]}$	0.728***	2.89	0.711***	2.89
$\beta_{[0,+9]}$	0.728***	2.90	0.711***	2.91
$\beta_{[0,+10]}$	0.729***	2.93	0.711***	2.94
N		485		

We use the bivariate form of Engle and Kroner's (1995) BEKK GARCH model to estimate the conditional betas. The model is estimated separately for the [-201,-1] and [0, +200] windows around announcement dates. The standard paired t-test and the non-parametric Wilcoxon signed rank test (WSRT) are used to judge whether the average pre-warning announcement beta, measured over the [-201, -1] window prior to the announcement date, is significantly different from the average post-warning beta, measured over a window of *S* days beginning one day after the event.

***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Table 3 Price reaction to profit warnings: The conditional market model approach

	Value (%)	t-statistic	Conditional versus unconditional	
			t-statistic	Z-score

Panel A: Negative warnings

	Value (%)	t-statistic	t-statistic	Z-score
$\overline{AR_0}$	-3.54	-16.14[***]	-4.97[***]	-5.49[***]
$\overline{AR_1}$	-0.16	-0.92	-4.73[***]	-4.82[***]
$\overline{CAR}_{[1,2]}$	0.04	0.18	-6.52[***]	-5.80[***]
$\overline{CAR}_{[1,3]}$	-0.02	-0.07	-8.27[***]	-7.15[***]
$\overline{CAR}_{[1,4]}$	-0.03	-0.10	-8.14[***]	-7.25[***]
$\overline{CAR}_{[1,5]}$	-0.01	-0.04	-8.68[***]	-7.76[***]
$\overline{CAR}_{[1,6]}$	0.01	0.03	-8.60[***]	-7.81[***]
$\overline{CAR}_{[1,7]}$	-0.06	-0.18	-8.74[***]	-7.92[***]
$\overline{CAR}_{[1,8]}$	-0.16	-0.44	-8.97[***]	-8.18[***]
$\overline{CAR}_{[1,9]}$	-0.17	-0.44	-9.27[***]	-8.39[***]
$\overline{CAR}_{[1,10]}$	-0.32	-0.79	-9.05[***]	-8.08[***]
N		1238		

Panel B: Positive warnings

Conditional versus unconditional

	Value (%)	t-statistic	t-statistic	Z-score
$\overline{AR_0}$	4.11	12.87[***]	4.43[***]	5.73[***]
$\overline{AR_1}$	-0.67	-3.96[***]	5.59[***]	5.68[***]
$\overline{CAR}_{[1,2]}$	-0.75	-3.10[***]	7.20[***]	7.21[***]
$\overline{CAR}_{[1,3]}$	-0.67	-2.37[***]	7.76[***]	8.15[***]
$\overline{CAR}_{[1,4]}$	-0.67	-2.23[***]	7.79[***]	7.89[***]
$\overline{CAR}_{[1,5]}$	-0.85	-2.60[***]	7.41[***]	8.29[***]
$\overline{CAR}_{[1,6]}$	-0.97	-2.70[***]	8.12[***]	8.24[***]
$\overline{CAR}_{[1,7]}$	-1.05	-2.73[***]	8.44[***]	8.51[***]
$\overline{CAR}_{[1,8]}$	-1.12	-2.80[***]	8.31[***]	8.43[***]
$\overline{CAR}_{[1,9]}$	-1.27	-3.06[***]	8.14[***]	8.35[***]
$\overline{CAR}_{[1,10]}$	-1.19	-2.73[***]	8.11[***]	8.38[***]
N		485		

To account for the potential effect of changes in beta on the abnormal returns around profit warnings, we estimate conditional beta-adjusted abnormal returns, $AR_{i,t}{}^c$, as follows:

$$AR_{i,t} = R_{i,t} - (\widehat{\alpha_h} + \widetilde{\beta_{i,t}} R_{m,t})$$

where $\beta_{i,t}$ is a time-varying beta estimated using the bivariate form of Engle and Kroner's (1995) BEKK GARCH model, which is estimated separately for the [-201, -1] and [0, +200] windows around the announcement dates. The average conditional beta-adjusted abnormal returns, $\overline{AR_t^c}$, are calculated by

$$\overline{AR_t} = \frac{\sum_{i=1}^{N} AR_{i,t}}{N}.$$

The time-varying beta-adjusted cumulative abnormal return of stock i over a window of S days starting one day after the event is given by

$$CAR_{i,s} = \sum_{t=1}^{S} AR_{i,t}.$$

The average time-varying beta-adjusted cumulative abnormal return over a window of S days beginning one day after the shock and across N stocks is computed by $\overline{CAR_s} = \frac{1}{N}\sum_{i=1}^{N} CAR_{i,s}$.

The standard t-test is used to assess the statistical significance of the price effect; ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Table 4 Price reaction to profit warnings: The role of event-induced variance and conditional heteroskedasticity

	Panel A: Negative warnings			
			Conditional versus unconditional	
	Value (%)	t-statistic	t-statistic	Z-score
$\overline{AR_0}$	-3.48	-7.66[***]	0.18	4.93[***]
$\overline{AR_1}$	0.00	-0.50	0.01	2.19[**]
$\overline{CAR}_{[1,2]}$	0.03	-1.16	1.89[*]	0.94
$\overline{CAR}_{[1,3]}$	-0.04	-1.30	2.49[**]	1.30
$\overline{CAR}_{[1,4]}$	-0.10	-0.28	2.55[**]	0.75
$\overline{CAR}_{[1,5]}$	0.02	-0.78	2.61[***]	1.32
$\overline{CAR}_{[1,6]}$	0.12	0.87	2.48[**]	0.88
$\overline{CAR}_{[1,7]}$	0.22	0.11	2.25[**]	1.31
$\overline{CAR}_{[1,8]}$	0.10	0.33	2.64[***]	1.04
$\overline{CAR}_{[1,9]}$	0.04	0.10	3.21[***]	1.97[**]
$\overline{CAR}_{[1,10]}$	0.14	0.95	2.62[***]	1.52
N		1238		

	Panel B: Positive warnings			
			Conditional versus unconditional	
	Mean (%)	t-statistic	t-statistic	Z-score
$\overline{AR_0}$	3.92	4.26[***]	-0.06	-4.05[***]
$\overline{AR_1}$	-0.85	-1.27	0.14	-4.76[***]
$\overline{CAR}_{[1,2]}$	-0.39	-1.33	-5.13[***]	-6.13[***]
$\overline{CAR}_{[1,3]}$	-0.27	-2.31[**]	-4.76[***]	-6.05[***]
$\overline{CAR}_{[1,4]}$	-0.19	-2.96[***]	-4.67[***]	-5.06[***]
$\overline{CAR}_{[1,5]}$	-0.15	-2.33[**]	-5.34[***]	-5.73[***]
$\overline{CAR}_{[1,6]}$	-0.25	-4.04[***]	-5.20[***]	-6.28[***]
$\overline{CAR}_{[1,7]}$	-0.14	-3.71[***]	-5.39[***]	-6.39[***]
$\overline{CAR}_{[1,8]}$	-0.17	-3.74[***]	-5.78[***]	-6.54[***]
$\overline{CAR}_{[1,9]}$	-0.18	-3.26[***]	-6.22[***]	-6.86[***]
$\overline{CAR}_{[1,10]}$	-0.17	-3.72[***]	-6.01[***]	-6.72[***]
N		485		

We use Savickas' (2003) model to estimate the abnormal returns

$$\begin{cases} R_{it} = \alpha_i + \beta_i R_{mt} + \gamma_{in} D_{in} + \varepsilon_{it}; \ \varepsilon_{it} \left| \Omega_{it-1} \sim N(0, h_{it}^2) \right. \\ h_{it}^2 = \varphi_i + \psi_i h_{it-1}^2 + \theta_i \varepsilon_{it-1}^2 + \phi_{in} D_{in} \end{cases}$$

where ε_{it} is a residual term, with a mean of zero and a time-varying variance h_{it}^2 assumed to follow a GARCH (1,1) process. The rest of the variables are defined as previously. The parameter γ_{in} reflects the abnormal returns around the event and the parameter ϕ_{in} captures the event-induced residual variance. We use the following statistics to account for the stochastic behavior of volatility during both event and non-event periods:

$$test = \sum_{i=1}^{N} \frac{S_{it}}{N} \bigg/ \sqrt{\frac{1}{N(N-1)} \sum_{i=1}^{N} \left(S_{i,t} - \sum_{j=1}^{N} S_{j,t}/N \right)^2}, \quad \text{where } S_{it} = \frac{\widehat{\gamma_{in}}}{\sqrt{\widehat{h_{in}^2}}}$$

where $\widehat{\gamma_{in}}$ is the estimated mean abnormal return of security i on a given day or window and $\widehat{h_{in}^2}$ is the estimated standard deviation of the abnormal return on a given day (we use the average of $\widehat{h_{it}^2}$ when abnormal returns are estimated over a window). The test statistic presented in Eq.(15) follows the Student t-distribution with $N - 1$ degrees of freedom.

[***], [**] and [*] indicate significance at 1%, 5% and 10%, respectively.

Table 5 Price reaction to profit warnings: The role of event-induced variance, conditional heteroskedasticity and time-varying betas

| | Panel A: Negative warnings | | | |
| | | | Conditional versus unconditional | |
	Value (%)	t-statistic	t-statistic	Z-score
$\overline{AR_0}$	-3.46	-5.95	0.25	1.89[*]
$\overline{AR_1}$	0.44	1.11	-1.11	1.22
$\overline{CAR}_{[1,2]}$	0.28	-0.63	0.72	-0.12
$\overline{CAR}_{[1,3]}$	-0.04	-1.64	2.57[**]	1.32
$\overline{CAR}_{[1,4]}$	0.32	1.09	0.76	0.09
$\overline{CAR}_{[1,5]}$	0.00	-0.53	2.63[***]	1.38
$\overline{CAR}_{[1,6]}$	0.23	2.14[**]	2.07[**]	0.82
$\overline{CAR}_{[1,7]}$	0.12	1.16	2.59[***]	1.35
$\overline{CAR}_{[1,8]}$	0.16	0.10	2.53[**]	1.00
$\overline{CAR}_{[1,9]}$	0.10	1.16	3.00[***]	1.72[*]
$\overline{CAR}_{[1,10]}$	0.05	0.30	2.89[***]	1.75[*]
N			1238	
	Panel B: Positive warnings			
			Conditional versus unconditional	
	Value (%)	t-statistic	t-statistic	Z-score
$\overline{AR_0}$	3.88	4.19	0.14	-3.47[***]
$\overline{AR_1}$	-0.92	-1.79[*]	0.54	-4.00[***]
$\overline{CAR}_{[1,2]}$	-0.57	-2.23[**]	-2.71[***]	-5.43[***]
$\overline{CAR}_{[1,3]}$	-0.34	-3.04[***]	-4.26[***]	-5.50[***]
$\overline{CAR}_{[1,4]}$	-0.15	-3.47[***]	-4.59[***]	-4.71[***]
$\overline{CAR}_{[1,5]}$	-0.09	-2.40[**]	-5.36[***]	-5.74[***]
$\overline{CAR}_{[1,6]}$	-0.19	-3.77[***]	-5.30[***]	-6.27[***]
$\overline{CAR}_{[1,7]}$	-0.25	-4.96[***]	-5.17[***]	-6.12[***]
$\overline{CAR}_{[1,8]}$	-0.16	-3.73[***]	-5.74[***]	-6.56[***]
$\overline{CAR}_{[1,9]}$	-0.12	-3.14[***]	-6.29[***]	-6.93[***]
$\overline{CAR}_{[1,10]}$	-0.16	-4.35[***]	-6.07[***]	-6.76[***]
N			485	

We allow the beta parameter in Savickas' (2003) model to vary over time. Specifically, we estimate the abnormal returns as follows:

$$\begin{cases} R_{it} = \alpha_i + \beta_{it} R_{mt} + \gamma_{in} D_{in} + \varepsilon_{it}; \ \varepsilon_{it} \left| \Omega_{it-1} \sim N(0, h_{it}^2) \right. \\ h_{it}^2 = \varphi_i + \psi_i h_{it-1}^2 + \theta_i \varepsilon_{it-1}^2 + \phi_{in} D_{in} \end{cases}$$

where ε_{it} is a residual term, with a mean of zero and a time-varying variance h_{it}^2 assumed to follow a GARCH (1,1) process, β_{it} is the time-varying beta estimated from the BEKK GARCH model, and the rest of the variables are defined as previously. The parameter γ_{in} reflects the abnormal returns around the event and the parameter ϕ_{in} captures the event-induced residual variance. We use the following statistics to account for the stochastic behavior of volatility during both event and non-event periods:

$$test = \sum_{i=1}^{N} \frac{S_{it}}{N} \Big/ \sqrt{\frac{1}{N(N-1)} \sum_{i=1}^{N} \left(S_{i,t} - \sum_{j=1}^{N} S_{j,t}/N \right)^2}, \quad \text{where } S_{it} = \frac{\widehat{\gamma_{in}}}{\sqrt{\widehat{h_{in}^2}}}$$

where $\widehat{\gamma_{in}}$ is the estimated mean abnormal return of security *i* on a given day or window and $\widehat{h_{in}^2}$ is the estimated standard deviation of the abnormal return on a given day (we use the average of $\widehat{h_{it}^2}$ when abnormal returns are estimated over a window). The test statistic presented in Eq.(15) follows a Student t-distribution with $N-1$ degrees of freedom. [***], [**] and [*] indicate significance at 1%, 5% and 10%, respectively.

Table 6 Multivariate regressions

	AR_1	$CAR_{[1,2]}$	$CAR_{[1,3]}$	$CAR_{[1,4]}$	$CAR_{[1,5]}$	$CAR_{[1,6]}$	$CAR_{[1,7]}$	$CAR_{[1,8]}$	$CAR_{[1,9]}$	$CAR_{[1,10]}$
Constant	-4.57**	-4.61**	-1.05	-0.74	-0.93	-0.67	-0.9	-0.6	-0.96*	-0.51
	(-2.32)	(-2.01)	(-1.05)	(-0.56)	(-0.89)	(-0.92)	(-1.30)	(-1.13)	(-1.82)	(-1.04)
AR_0	-1.94	-5.99	-4.65**	-3.59	-3.25	0.1	-0.94	-0.77	-0.7	-0.76
	(-0.48)	(-1.64)	(-2.46)	(-1.49)	(-1.37)	(0.08)	(-0.75)	(-0.83)	(-0.74)	(-0.91)
$lnMV$	0.54**	0.322	0.07	-0.05	0.05	0.08	0.03	0.03	0.06	0.04
	(2.33)	(1.46)	(0.74)	(-0.43)	(0.49)	(1.09)	(0.55)	(0.57)	(1.12)	(0.85)
$BTMV$	-0.015	0.023	-0.00	-0.01**	-0.02	-0.00	0.01	-0.01	-0.01	-0.01
	(-0.51)	(-0.74)	(-1.33)	(-2.50)	(-1.33)	(-0.12)	(0.56)	(-1.21)	(-1.36)	(-0.55)
$AvgTO$	-1.77	-0.243	-0.442	-0.35	-0.14	0.241	-0.457	0.157	-0.182	-0.22
	(-1.05)	(-0.16)	(-0.58)	(-0.48)	(-0.25)	(-0.42)	(-1.00)	(0.33)	(-0.46)	(-0.49)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	484	484	484	484	484	484	484	484	484	484
Adjusted R^2	0.008	0.019	0.016	0.004	0.005	0.007	0.012	0.011	0.012	0.001

This table reports the results of the following pooled OLS regression:

$$CAR_{is} = \alpha_0 + \alpha_1 \, AR_{0i} + \sum_k \alpha_{ik} \, Control_i^k + IndustryDummies + YearDummies + \varepsilon,$$

where CAR_{is} is firm i's average cumulative abnormal return over windows of S days following positive warnings; AR_{0i} is firm i's average abnormal return on the event date (both AR_{0i} and CAR_{is} are adjusted for the time-varying betas, event-adjusted variance and conditional heteroskedasticity); $Control_i^k$ is a vector of control variables, which include a set of firm-specific variables that are deemed to influence stock returns. These variables include the book-to-market ratio ($BTMV_i$), the natural logarithm of stock i's market capitalization measure ($lnMV_i$) and the average turnover – i.e., the daily trading volume divided by the number of shares outstanding ($AvgTO_i$). $BTMV_i$ and $lnMV_i$ are measured 11 days prior to positive warnings, while $AvgTO_i$ is computed over the [-105, -6] windows prior to the positive warnings. Industry and year dummies are included to control for the industry and year fixed effects. We also correct standard errors for firm-level clustering.

The figures in parentheses are the t-statistics.

The regression coefficients are multiplied by 10^2.

***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Table 7 Alternative time-varying beta estimates

Panel A: Time-varying betas

	GARCH				TGARCH				EGARCH			
	Negative warn		Positive warn		Negative warn		Positive warn		Negative warn		Positive warn	
	Mean (%)	t-stat	Mean (%)	t-stat	Mean (%)	t-stat	Mean (%)	t-stat	Mean (%)	t-stat	Mean (%)	t-stat
$\beta_{[-201,-1]}$	0.64		0.73		0.64		0.73		0.63		0.66	
$\beta_{[0,+1]}$	0.67**	2.44	0.89***	7.96	0.66	1.53	0.88***	7.59	0.62	-0.19	0.71**	2.03
$\beta_{[0,+2]}$	0.67**	2.43	0.88***	8.27	0.66	1.33	0.87***	7.81	0.63	0.15	0.70*	1.81
$\beta_{[0,+3]}$	0.66**	2.19	0.87***	8.22	0.65	0.98	0.87***	7.82	0.62	-0.29	0.69	1.51
$\beta_{[0,+4]}$	0.66*	1.82	0.87***	8.08	0.65	0.66	0.86***	7.75	0.62	-0.48	0.69	1.25
$\beta_{[0,+5]}$	0.66	1.58	0.86***	7.90	0.65	0.40	0.86***	7.63	0.62	-0.63	0.68	1.06
$\beta_{[0,+6]}$	0.65	1.36	0.85***	7.69	0.64	0.21	0.85***	7.49	0.62	-0.76	0.68	0.92
$\beta_{[0,+7]}$	0.65	1.18	0.85***	7.42	0.64	0.09	0.85***	7.23	0.62	-0.81	0.68	0.80
$\beta_{[0,+8]}$	0.65	1.02	0.84***	7.18	0.64	0.00	0.84***	6.98	0.62	-0.81	0.67	0.69
$\beta_{[0,+9]}$	0.65	0.88	0.84***	7.02	0.64	0.18	0.84***	6.82	0.61	-0.97	0.67	0.59
$\beta_{[0,+10]}$	0.65	0.81	0.84***	6.90	0.64	0.32	0.84***	6.70	0.61	-1.11	0.67	0.52
MSE	12.54x10^{-4}		23.92x10^{-4}		12.53x10^{-4}		23.94x10^{-4}		50.10x10^{-4}		50.47x10^{-4}	

Panel B: Time-varying beta-adjusted ARs and CARs

	GARCH				TGARCH				EGARCH			
	Negative warn		Positive warn		Negative warn		Positive warn		Negative warn		Positive warn	
	Value (%)	t-stat	Value (%)	t-stat	Value (%)	t-stat	Value (%)	t-stat	Value (%)	t-stat	Value (%)	t-stat
$\overline{AR}_0$	-3.45***	-16.76	3.93***	12.47	-3.45***	-16.76	3.93***	12.47	-3.46***	-16.21	3.98***	12.04
$\overline{AR}_1$	0.01	0.04	-0.83***	-5.00	0.01	0.04	-0.83***	-5.00	-0.03	-0.16	-0.85***	-5.06
$\overline{CAR}_{[1,2]}$	0.40*	1.74	-1.14***	-4.68	0.40*	1.74	-1.14***	-4.68	0.35	1.51	-1.12***	-4.79
$\overline{CAR}_{[1,3]}$	0.49*	1.89	-1.22***	-4.31	0.49*	1.89	-1.22***	-4.31	0.45*	1.71	-1.15***	-4.08
$\overline{CAR}_{[1,4]}$	0.54*	1.86	-1.32***	-4.30	0.54*	1.86	-1.32***	-4.30	0.55*	1.89	-1.27***	-4.12
$\overline{CAR}_{[1,5]}$	0.72**	2.21	-1.63***	-4.89	0.72**	2.21	-1.63***	-4.89	0.71**	2.14	-1.58***	-4.73
$\overline{CAR}_{[1,6]}$	0.87**	2.45	-1.89***	-5.04	0.87**	2.45	-1.89***	-5.04	0.90**	2.48	-1.80***	-4.73
$\overline{CAR}_{[1,7]}$	0.98***	2.58	-2.05***	-5.10	0.98**	2.58	-2.05***	-5.10	0.96**	2.46	-1.98***	-4.83
$\overline{CAR}_{[1,8]}$	1.04***	2.66	-2.33***	-5.51	1.04**	2.66	-2.33***	-5.51	1.04***	2.59	-2.26***	-5.22
$\overline{CAR}_{[1,9]}$	1.24***	2.97	-2.61***	-5.99	1.24**	2.97	-2.61***	-5.99	1.20***	2.82	-2.57***	-5.75
$\overline{CAR}_{[1,10]}$	1.18***	2.73	-2.68***	-5.87	1.18**	2.73	-2.68***	-5.87	1.13***	2.54	-2.54***	-5.46

Following Faff et al. (2000), we estimate a time series of conditional betas, β_{it}^G, for a stock i as

$$\beta_{it}^G = \frac{\rho_{im}\sigma_{it}}{\sigma_{mt}}$$

where σ_{it} and σ_{mt} are the time-varying conditional variances of the stock and the market, respectively, and ρ_{im} is the covariance between the stock and market returns, which is assumed to be constant. The time-varying conditional variances (σ_{it} and σ_{mt}) are modelled using the standard GARCH (1,1), TGARCH(1,1) and EGARCH(1,1). We use the in-sample mean squared error of forecasts, or $MSE_i = \sum(R_{it}^* - R_{it})^2/T$, to assess the accuracy of each forecasted beta series (including those obtained from the BEKK model). Here, R_{it}^* are the predicted values of stock i's return series generated from the single index model with timing-varying betas, and

T is the number of days in the estimation period. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Table 8 Subperiod analysis

	Panel A: Price reaction to profit warnings: July 2007 to July 2009							
	Market model		Time-varying beta adjustment (BEKK)		Savickas (2003) model		Savickas (2003) with time-varying betas	
	Negative warning	Positive warning	Negative warning	Positive warning	Negative warning	Positive warning	Negative warning	Positive warning
$\overline{AR}_0$	-3.31***	6.04***	-3.47***	6.08***	-2.94***	6.79***	-3.44***	6.01***
$\overline{AR}_1$	0.14	-1.40***	0.02	-1.19***	0.39	-1.34	-0.01	-1.05**
$\overline{CAR}_{[1,2]}$	0.85**	-2.28***	0.60*	-1.95***	0.07	-0.87	-0.03**	-0.76
$\overline{CAR}_{[1,3]}$	1.06***	-2.40***	0.60	-1.91***	0.06	-0.80**	-0.06	-0.78**
$\overline{CAR}_{[1,4]}$	1.16***	-2.63***	0.54	-2.10**	-0.13	-0.68**	0.15	-0.81***
$\overline{CAR}_{[1,5]}$	1.49***	-2.37***	0.69	-1.84**	0.01	-0.18	-0.17	-0.27
$\overline{CAR}_{[1,6]}$	1.79***	-2.99***	0.87*	-2.31**	0.19	-0.32**	0.10	-0.27**
$\overline{CAR}_{[1,7]}$	2.00***	-3.14***	0.92*	-2.34**	0.31	-0.26**	0.07	-0.30**
$\overline{CAR}_{[1,8]}$	2.21***	-3.99***	1.03*	-3.04***	0.13	-0.34**	0.12	-0.35**
$\overline{CAR}_{[1,9]}$	2.45***	-4.14***	1.10*	-3.27***	0.12	-0.39**	0.00	-0.27*
$\overline{CAR}_{[1,10]}$	2.37***	-4.09***	0.86	-3.17***	0.20	-0.30**	0.08	-0.23*
N	718	98	718	98	718	98	718	98

	Panel B: Price reaction to profit warnings: August 2009 to July 2012							
	Market model		Time-varying beta adjustment (BEKK)		Savickas (2003) model		Savickas (2003) with time-varying betas	
	Negative warning	Positive warning	Negative warning	Positive warning	Negative warning	Positive warning	Negative warning	Positive warning
$\overline{AR}_0$	-3.61***	3.39***	-3.53***	3.44***	-4.27***	3.20***	-3.44***	3.36***
$\overline{AR}_1$	-0.18	-0.68***	-0.03	-0.56***	-0.53	-0.72	-0.01	-0.91
$\overline{CAR}_{[1,2]}$	-0.24	-0.83***	-0.06	-0.72***	-0.02	-0.27**	-0.03**	-0.52*
$\overline{CAR}_{[1,3]}$	-0.32	-0.91***	-0.13	-0.74**	-0.19	-0.14	-0.06	-0.23**
$\overline{CAR}_{[1,4]}$	-0.37	-0.98***	-0.07	-0.75**	-0.07	-0.06**	0.15	0.01**
$\overline{CAR}_{[1,5]}$	-0.38	-1.42***	-0.09	-1.14***	0.01	-0.14**	-0.17*	-0.04**
$\overline{CAR}_{[1,6]}$	-0.43	-1.60***	-0.06	-1.25***	0.01	-0.23***	0.10	-0.18***
$\overline{CAR}_{[1,7]}$	-0.49	-1.77***	-0.08	-1.32***	0.08	-0.11***	0.07	-0.23***
$\overline{CAR}_{[1,8]}$	-0.61	-1.90***	-0.15	-1.37***	0.07	-0.13***	0.12	-0.11***
$\overline{CAR}_{[1,9]}$	-0.49	-2.21***	0.00	-1.62***	-0.08	-0.13***	0.00	-0.09***
$\overline{CAR}_{[1,10]}$	-0.53	-2.32***	0.02	-1.67***	0.06	-0.14***	0.08	-0.14***
N	522	387	522	387	522	387	522	387

This table reports the average abnormal returns ($\overline{AR}_i$) and the average cumulative abnormal returns ($\overline{CAR}_s$) from the standard market model (Section 3.1), the market model with time-varying betas (Section 3.2), the Savikas model (Section 3.3) and the Savikas model with time-varying betas (Section 3.4), separately for the periods July 2007 to July 2009 and August 2009 to July 2012.

***, ** and * indicate significance at 1%, 5% and 10%, respectively.
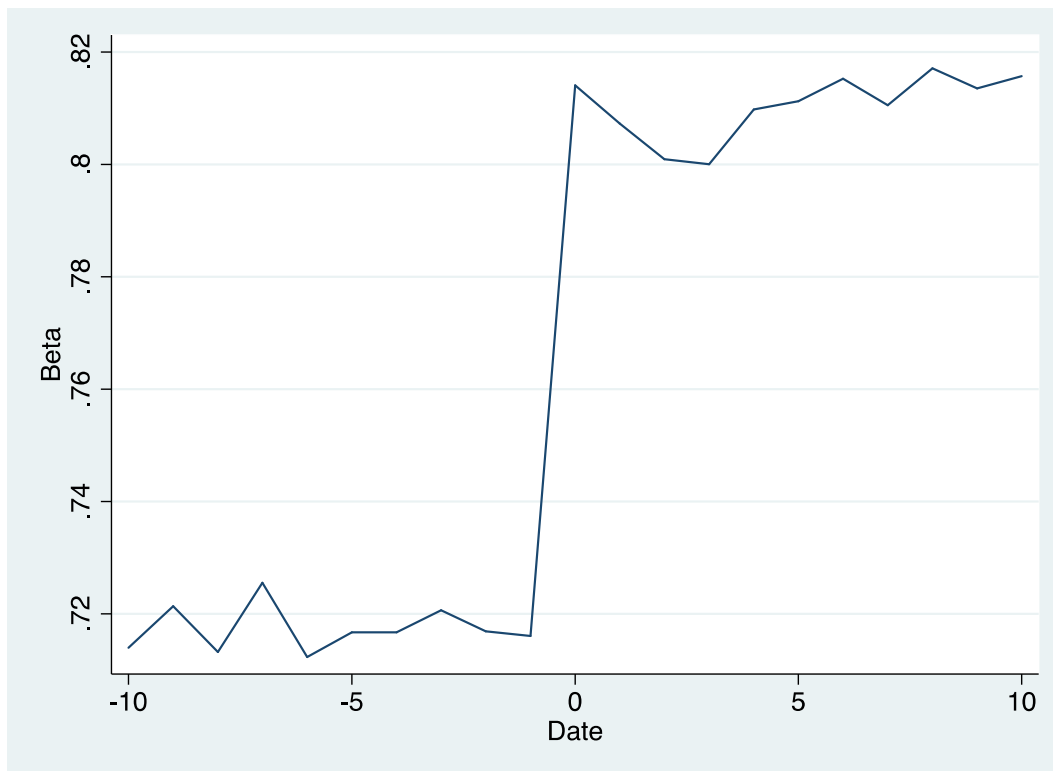
Figure 1 Changes in beta around positive warnings

Figure 2 Changes in beta around negative warnings