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Stock index reaction to large price changes: Evidence from major Asian stock indexes

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ABSTRACT

We examine the short-term price behavior of ten Asian stock market indexes following large price changes or “shocks”. Under the standard OLS regression, there is stronger support for return continuations particularly following positive and negative price shocks of less than 10% in absolute size. The results under the GJR-GARCH method provide stronger support for market efficiency, especially for large price shocks. For example, for the Hong Kong stock index, negative shocks of less than -5% but more than -10% generate a significant one day cumulative abnormal return (CAR) of -0.754% under the OLS method, but an insignificant CAR of 0.022% under the GJR-GARCH. We find no support for the uncertainty information hypothesis. Furthermore, the CARs following the period after the Asian financial crisis adjust more quickly to price shocks.

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1. Introduction

Several empirical studies on short-term price changes or “shocks” show that investors overreact to the arrival of new information about stock prices. Specifically, [Bremer and Sweeney \(1991\)](#) find that large negative price changes give rise to overreaction in U.S. stocks. This price behavior is not consistent with the efficient market hypothesis (EMH). [Bowman and Iverson \(1998\)](#) also find support for the overreaction hypothesis following large weekly price changes in New Zealand stocks, whilst [Ferri and Chung-Ki \(1996\)](#) observe a similar pattern following large one day price changes in the S&P500 index. [Cox and Peterson \(1994\)](#) also find support for the overreaction hypothesis in U.S. stocks. However, most of the price reversals disappear after accounting for the bid-ask bounce. Similarly, [Atkins and Dyl \(1990\)](#) find overreaction in U.S. daily stock prices but they conclude in favor of market efficiency after accounting for the bid-ask spread and market liquidity. In contrast, [Park \(1995\)](#) finds support for overreaction in U.S. stocks and shows that the

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price reversals are not fully explained by the bid-ask bounce (see also, Bremer et al., 1997). Recently, Lasfer et al. (2003) find support for return continuations in stock price indexes which they attribute to momentum behavior in returns. If short-term return continuations are due to investor biases, these biases should give rise to a price drift as information uncertainty increases (see, Zhang, 2006).

Brown et al. (1988) argue that their uncertain information hypothesis (UIH), provides a richer description of short-term price behavior. Under the UIH, the arrival of new market-wide information has two simultaneous effects on a security's price: i) it makes the stock price adjust to the content of impending news; and, ii) it creates a transitory systematic risk component.¹ The transitory risk component accounts for the condition that investors often set prices before the full ramification of new and impending information is known. Since risk-averse investors require a higher return for a higher level of risk, the asset's price following the arrival of new information will be lower than its expected value, given the perceived risk associated with the new event. The UIH further predicts that after adjusting for the risk element of the news, the abnormal return (AR) will be zero in line with the EMH. An important advantage of the UIH is that it provides a direct test of the behavior of both risk and expected return around large price changes, unlike other approaches.

Brown et al. (1988) find support for the UIH in the U.S. stock market. Specifically, they find that both post-event average returns and volatility increase after the arrival of positive and negative unexpected news. Schnusenberg and Madura (2001) also find support for the UIH, although they are not specifically concerned with large price shocks. Using the symmetric generalized autoregressive conditional heteroscedastic (GARCH) estimation method, Ajayi et al. (2006) also find support for the UIH in U.S. stock indexes.²

Overall, prior empirical studies do not provide conclusive evidence as to whether overreaction, underreaction, market efficiency, or uncertainty information best explains short-term price behavior.³ This weakness of prior studies may be partly due to their research designs. For example, we show later that the magnitude of the price shock is an important factor contributing to differences in the results obtained. We also find that the choice of the estimation method leads to differences in the results.⁴

This empirical study examines the short-term price behavior of ten Asian stock market indexes following large price shocks.⁵ We are specifically interested in the unexpected price impacts of positive and negative shocks under uncertainty.⁶ Most prior studies on short-term price behavior employ the standard OLS method to estimate the ARs. To provide a comparison with prior studies, we estimate the ARs using the standard OLS. However, to avoid the econometric problems associated with the standard OLS estimation method, we also estimate the ARs using the: i) symmetric GARCH, and ii) Glosten et al. (1993) threshold (asymmetric) GARCH, hereafter GJR-GARCH, estimation methods. Both the symmetric GARCH and the GJR-GARCH estimation methods allow us to capture the conditional volatility in returns.

There are several important aspects of our research design that deserve consideration. Firstly, Savickas (2003) shows that the use of the symmetric GARCH method to capture heteroscedasticity around event and non-event dates leads to substantially higher rejection rates of the false null hypothesis compared to previous approaches. Whilst the symmetric GARCH seeks to capture the effects of conditional volatility on the returns, the GJR-GARCH method seeks to capture both conditional volatility and asymmetry in returns. That is, in addition to the conditional volatility, the GJR-GARCH also controls for the likelihood that negative shocks have a larger impact on returns compared to positive shocks. The use of GARCH-based estimation methods also leads to greater estimation efficiency compared to the standard OLS method. If the variance of

¹ The UIH builds on earlier empirical work that shows that the volatility of stock returns increases around regularly scheduled firm-specific announcements (see, e.g., Kalay and Lowenstein, 1985).

² Ajayi et al. (2006) claim that their results are not sensitive to the type of GARCH model used.

³ To see this, we provide a summary of the main findings in Appendix A.

⁴ Most empirical studies employ the standard OLS estimation method (see e.g., Atkins and Dyl, 1990; Lasfer et al., 2003) despite its restrictive assumptions. In our study, we estimate the ARs using OLS and GARCH-based estimation methods.

⁵ Our study therefore differs from those studies concerned with both long-term (medium-term) price overreaction (momentum) associated with De Bondt and Thaler (1985) and Jegadeesh and Titman (1993), for example. Such studies are not concerned with price shocks and their methodological approach focuses mainly on portfolio rankings.

⁶ The events are considered to be unexpected since they are not necessarily centered around regularly scheduled financial and economic announcements. This does not mean that some expected events may not have been included in our analysis. The problem here is that we cannot practically observe all expected events for the stock indexes used in our study.

returns increases nearer the event period (see, e.g., Brown and Warner, 1980; Corrado, 1989) due to uncertainty, failure to capture event-induced variances in the returns can lead to invalid inferences.

Secondly, our estimates of ARs and volatility are both obtained using a dummy variable approach similar to that of Karafiath (1988). Karafiath's (1988) approach improves estimation efficiency relative to the two-stage residual method commonly employed in prior studies. Indeed, Karafiath (1988) shows that the dummy variable approach provides correct test statistics in a single step. Finally, unlike previous studies, we show that the magnitude of the price shock has an important effect on the result obtained.

To summarize our results, we find that the price reaction to shocks depends on both the magnitude and direction of the price shock.⁷ Whilst this result holds for all estimation methods, the magnitude of the cumulative ARs (CARs) is substantially different under the OLS and GARCH-based methods. Specifically, the CARs under the OLS method tend to be larger than those of the GARCH-based methods, except for very large negative shocks. Under the OLS method, the CARs following positive and negative shocks give support for return continuations particularly when the shocks are less than 10% in absolute value. In some cases, the CARs are significant for up to ten days. Larger shocks, particularly large negative shocks, are followed by overreaction. The GARCH-based results also provide support for return continuations, but mainly following positive shocks of more than 3% but less than 5%. However, the GARCH-based methods provide much stronger support for market efficiency (compared to the OLS method), particularly when the shocks are large. Our results do not support the UIH. Specifically, the post-event volatility of the ARs does not increase after the price shock. Finally, the CARs appear to adjust more quickly to price shocks after the Asian financial crisis.

2. Methodology

To be consistent with prior studies (see, e.g., Park, 1995; Atkins and Dyl, 1990), we identify the price shocks using the quantitative trigger value approach. A stock's price reaction to shocks can be successfully tested without reference to the specific type of announcement likely to impact on its price (see Brown et al., 1988). An event day is therefore identified on the basis of the magnitude of the continuously compounded raw return on index i at day t (or $R_{i,t}$). To identify positive price shocks at the time interval t , we use various price shock ranges, s_t^+ as follows: $+3\% < s_t^+ < +5\%$; $+5\% \leq s_t^+ < +10\%$; $+10\% \leq s_t^+ < +15\%$; and, $s_t^+ \geq +15\%$. Similarly, for negative price shocks at the time interval t , we use the price shock ranges, s_t^- as follows: $-3\% > s_t^- > -5\%$; $-5\% \geq s_t^- > -10\%$; $-10\% \geq s_t^- > -15\%$; and, $s_t^- \leq -15\%$. These trigger values are used for all estimation methods. In line with Karafiath (1988), we use a dummy variable to estimate both the event and post-event ARs.

Under the symmetric GARCH, the GJR-GARCH and OLS estimation methods, the ARs are estimated for stock index i thus:

$$R_{i,t} = \alpha_i + \varphi_{i,n} D_{t,n} + \varepsilon_{i,t}; \varepsilon_{i,t} | \Omega_{i,t-1} \sim N(0, h_{i,t}^2) \quad (1)$$

where α_i is a constant. The subscript $n \in [0, +N]$ of the variable $D_{t,n}$ which denotes the number of days after the event day t . $D_{t,0}$ is a dummy that equals 1 if t is the event day (day 0) and zero otherwise. $D_{t,1}$ is a dummy variable that equals 1 if t is first day after the event day or shock and zero otherwise. $D_{t,2}, D_{t,3}, \dots, D_{t,N}$ are dummy variables which take on values of 1 if $t \in [+1, +2], [+1, +3], \dots, [+1, +N]$, respectively, and zero otherwise. $\varphi_{i,n}$ is the coefficient for the abnormal return of the event day or window after the shock. $N(0, h_{i,t}^2)$ denotes a normal distribution with a mean of zero and a variance of $h_{i,t}^2$.⁸ The variance of $\varepsilon_{i,t}$ is assumed to be constant under the OLS estimation approach and time varying under the GARCH-based methods. $\Omega_{i,t-1}$ is the information set available to investors at time $t-1$ or earlier.

The post-event CARs associated with a window of length n days is estimated as $CAR_{i,n} = \varphi_{i,n} \times n$ for each stock index, i . Thus the day one CAR, $CAR_{i,1}$, is defined as $CAR_{i,1} = \varphi_{i,1} \times 1$, $CAR_{i,2} = \varphi_{i,2} \times 2, \dots, CAR_{i,N} = \varphi_{i,N} \times N$.

⁷ Earlier results show that the price reaction is generally robust to variation in the magnitude of the price shock. Bremer and Sweeney (1991), for example, alter their basic -10% trigger value to -7% and -15% without a corresponding change in their results. Howe (1986) also finds support for overreaction using trigger values of $\pm 50\%$. However, using trigger values of $\pm 20\%$ in incremental steps to $\pm 60\%$, Brown and Harlow (1988) find support for overreaction at short horizons and underreaction at long horizons.

⁸ Savickas (2003) indicates that the mean of the AR will be zero for the event window since ε_{t-1} is assumed to be zero by construction.

To complete the specification for the symmetric GARCH, we write the conditional variance for Eq. (1) as:

$$h_{i,t}^2 = \varpi_i + \alpha_i \varepsilon_{t-1}^2 + \beta_i h_{i,t-1}^2 + \gamma_{i,n} D_{t,n}. \quad (2)$$

In Eq. (2), the coefficient ϖ_i is the permanent component of the conditional variance. α_i and β_i are respectively the coefficients for the impacts of recent news and prior period volatility. The dummy coefficient $\gamma_{i,n}$ captures the abnormal conditional volatility for the event window following the shock. A positive (negative) coefficient for $\gamma_{i,n}$ indicates an increase (a decrease) in the volatility of returns over the event window. Brown et al. (1988) estimate the change in volatility using the return variances pre- and post the event dates. Our use of GARCH-based methods allows us to: i) do away with some of the restrictive assumptions of OLS; and ii) account for the volatility changes following the event.

The conditional variance for the GJR-GARCH method can be written as:

$$h_{i,t}^2 = \varpi_i + \alpha_i \varepsilon_{t-1}^2 + \beta_i h_{i,t-1}^2 + \eta_i I_{i,t-1} \varepsilon_{i,t-1}^2 + \gamma_{i,n} D_{t,n}. \quad (3)$$

In Eq. (3), η_i is the coefficient for asymmetry. That is, $I_{i,t-1}$ is an indicator variable that equals one if $\varepsilon_{t-1} < 0$ and zero otherwise. The remaining parameters in Eq. (3) are similar to those in Eq. (2). Throughout this study, we avoid potentially confounding effects by ignoring any shock that occurs within the 10 day window following the shock.

3. Data

To test our hypotheses, we analyze the stock price indexes of 10 major Asian countries. We focus on the stock price indexes of these countries since Lasfer et al. (2003) indicate that negative shocks have a more pronounced effect on the stock indexes of emerging markets compared with those of developed markets. All the price indexes are taken from DataStream. They start from various dates with January 1, 1971 (see Table 1) being the earliest and end on December 31, 2005. The index prices are transformed to natural logarithms prior to estimation.

4. Empirical results

4.1. Frequency of the shocks

Using the OLS estimation method, we show the frequency of both positive and negative shocks in Table 1. The table shows that positive shocks are more common than negative shocks. The greater occurrence of positive shocks, perhaps reflects the period of real economic growth following equity market liberalization in those countries (see Bekaert et al., 2005). As expected, small positive and negative shocks are more common than large positive and negative shocks. Specifically, price shocks within the range of $+3\% < s_t^+ < +5\%$ and $-3\% > s_t^- > -5\%$ account for up to 73.09% of the total number of shocks. The corresponding percentage for shocks within the range of $+10\% \leq s_t^+ < +15\%$ and $-10\% \geq s_t^- > -15\%$ is 2.49%. Large shocks tend to occur with decreasing frequency such that shocks of $s_t^+ \geq +15\%$ and $s_t^- \leq -15\%$ are very rare. We show later that small shocks are followed by return continuations, whereas large shocks are often followed by both overreaction and market efficiency. Relative to the total number of observations, the frequency of the shocks is greatest for the Taiwanese and Thai stock indexes, whilst it is lowest for the Indonesian and Malaysian stock indexes.

4.2. Positive and negative shocks under the OLS method

Table 2 shows the CARs for each stock index under the OLS method.⁹ Positive shocks within the range of $+3\% < s_t^+ < +5\%$ are followed by positive and significant CARs, whilst negative shocks within the range of

⁹ Throughout this study, the CARs are estimated from day one to day ten. For most of this paper, we present the CARs from day one to day five as well as day ten, but discuss the results over the entire ten day window. Also, since positive shocks of $s_t^+ \geq +15\%$ and negative shocks of $s_t^- \leq -15\%$ are relatively uncommon, the CARs following those shock sizes are included in the results for shock sizes of $s_t^+ \geq +10\%$ and $s_t^- \leq -10\%$. Other results not fully presented are available on request.

Table 1

Frequency of positive and negative shocks of 5% or more under the OLS.

Country	Start date	Frequency of positive shocks for various trigger values							Frequency of negative shocks for various trigger values					
		Total Obs.	3% < $s_t^+ < 5\%$	5% ≤ $s_t^+ < 10\%$	10% ≤ $s_t^+ < 15\%$	$s_t^+ \geq +$ 15%	Total	Mean AR	− 3% > $s_t^- > -5\%$	− 5% ≥ $s_t^- > -10$	− 10 ≥ $s_t^- > -15\%$	$s_t^- \geq -15\%$	Total	Mean AR
Hong Kong (HNGKNGI)	Jan., 1, 1971	9130	162	59	7	1	229	4.80 ^a	150	57	8	2	217	−5.12 ^a
India (IBOMBSE)	Jan., 2, 1987	4955	82	27	1	1	111	4.59 ^a	79	21	2	0	102	−4.53 ^a
Indonesia (JAKCOMP)	Apr., 4, 1983	5934	55	22	8	2	87	5.39 ^a	55	17	4	1	77	−5.06 ^a
Korea (KORCOMP)	Dec., 31, 1974	8088	122	38	1	0	161	4.33 ^a	113	42	3	1	159	−4.69 ^a
Malaysia (KLPCOMP)	Jan., 2, 1980	6782	73	19	4	2	98	4.79 ^a	71	26	5	2	104	−5.10 ^a
Pakistan (PKSE100)	Dec., 29, 1988	4436	70	18	1	0	89	4.30 ^a	59	18	1	0	78	−4.66 ^a
Philippines (MANCOMZ)	Sep., 8, 1987	4778	67	19	1	2	89	4.59 ^a	68	19	0	0	87	−4.49 ^a
Singapore (SNGPORI)	Jan., 4, 1985	5475	50	11	1	1	63	4.52 ^a	36	13	3	1	53	−5.39 ^a
Taiwan (TAIWGHT)	Jan., 5, 1971	9128	183	60	4	1	248	4.58 ^a	179	58	4	1	242	−4.64 ^a
Thailand (TOTMKTH)	Jan., 2, 1987	4955	103	41	4	0	148	4.70 ^a	91	32	1	0	124	−4.58 ^a
Total			967	314	32	10	1323	4.66 ^a	901	303	31	8	1243	−4.83 ^a

^a Denotes statistical significance at a 1-percent level. Statistical significance is determined using the standard *t*-statistic. The mean ARs are for all shocks greater than 3% of either sign. s_t^+ and s_t^- respectively denote the magnitude of positive and negative shocks at time *t*. The CARs are estimated over a window of ten days.

Table 2

OLS estimates of CARs following positive and negative shocks.

Country	Mean AR	CAR1	CAR2	CAR3	CAR4	CAR5	CAR10	Mean AR	CAR1	CAR2	CAR3	CAR4	CAR5	CAR10
<i>Panel A: Positive shocks of $+3\% < s_t^+ < +5\%$</i>								<i>Panel B: Negative shocks of $-3\% > s_t^- > -5\%$</i>						
Hong Kong	3.759 ^a	0.585 ^a	0.896 ^a	0.843 ^a	1.181 ^a	1.236 ^a	2.070 ^a	−3.856 ^a	−0.315 ^b	−0.458 ^b	−0.568 ^b	−0.812 ^b	−0.641 ^c	−1.37 ^a
India	3.686 ^a	−0.075	−0.107	0.208	0.456	0.940 ^b	0.662	−3.814 ^a	−0.223	−0.641 ^b	−0.630 ^b	−0.862 ^b	−0.968 ^b	−2.267 ^a
Indonesia	3.727 ^a	1.420 ^a	2.283 ^a	2.552 ^a	2.674 ^a	2.495 ^a	1.770 ^a	−3.789 ^a	−0.796 ^a	−1.285 ^a	−1.422 ^a	−1.352 ^a	−1.652 ^a	−2.021 ^a
Korea	3.693 ^a	0.204	0.265	0.116	0.288	0.193	0.094	−3.781 ^a	0.353 ^b	0.921 ^a	0.966 ^a	0.760 ^b	0.474	0.445
Malaysia	3.605 ^a	0.431 ^b	0.670 ^a	0.429	0.303	−0.048	−0.007	−3.683 ^a	−0.445 ^b	−0.575 ^b	−0.301	−0.248	0.313	−0.257
Pakistan	3.625 ^a	0.153	0.140	0.263	0.247	0.100	0.694	−3.827 ^a	−0.191	−0.257	−0.181	−0.315	−0.275	−1.412 ^b
Philippines	3.682 ^a	0.696 ^a	0.781 ^a	1.049 ^a	1.426 ^a	1.095 ^b	1.608 ^b	−3.876 ^a	−0.441 ^b	−0.577 ^b	−0.674 ^b	−0.861 ^b	−0.505	−0.103
Singapore	3.681 ^a	0.953 ^a	1.239 ^a	1.313 ^a	1.656 ^a	1.522 ^a	1.053 ^c	−3.669 ^a	−0.583 ^b	−1.177 ^a	−1.326 ^a	−1.719 ^a	−0.738	1.439 ^c
Taiwan	3.815 ^a	0.172	0.540 ^a	0.616 ^a	0.646 ^b	0.981 ^a	1.021 ^b	−3.817 ^a	0.084	−0.252	−0.688 ^a	−0.898 ^a	−0.957 ^a	−0.762
Thailand	3.748 ^a	0.734 ^a	1.059 ^a	1.162 ^a	1.393 ^a	1.336 ^a	1.412 ^b	−3.805 ^a	−0.653 ^a	−1.266 ^a	−1.345 ^a	−1.081 ^a	−1.708 ^a	−1.371 ^b
<i>Panel C: Positive shocks of $+5\% \leq s_t^+ < +10\%$</i>								<i>Panel D: Negative shocks of $-5\% \geq s_t^- > -10\%$</i>						
Hong Kong	6.593 ^a	0.367	0.199	0.970 ^b	0.900 ^c	0.196	−0.282	−6.556 ^a	−0.754 ^a	−0.341	−1.168 ^a	−2.438 ^a	−2.125 ^a	−1.950 ^b
India	6.595 ^a	0.201	−0.060	−0.531	−1.585 ^a	−1.291 ^c	−0.938	−6.615 ^a	−0.575 ^c	0.659	1.057 ^c	0.189	−0.354	−2.923 ^a
Indonesia	6.097 ^a	1.182 ^a	1.304 ^a	1.290 ^b	1.154 ^c	2.156 ^a	3.104 ^a	−6.443 ^a	0.311	1.681 ^a	1.153 ^c	0.948	0.708	2.887 ^b
Korea	6.224 ^a	1.183 ^a	1.365 ^a	1.572 ^a	1.149 ^b	1.044 ^c	2.022 ^b	−6.294 ^a	−0.488 ^a	−1.310 ^a	0.091	0.162	0.795	1.481 ^c
Malaysia	6.336 ^a	2.600 ^a	2.371 ^a	1.048 ^c	1.494 ^b	0.533	−0.717	−6.301 ^a	0.325	0.332	1.876 ^a	2.271 ^a	1.801 ^a	0.368
Pakistan	6.434 ^a	−0.848 ^b	−1.536 ^a	−1.318 ^b	−0.809	−1.189	−1.601	−6.927 ^a	0.201	−0.333	−1.196 ^c	−1.809 ^b	−1.470 ^c	−4.510 ^a
Philippines	6.302 ^a	0.684 ^b	−0.479	−0.453	−0.142	0.185	3.611 ^a	−6.669 ^a	−0.915 ^a	−0.453	−0.002	0.118	0.336	0.201
Singapore	6.381 ^a	1.407 ^a	1.798 ^a	2.277 ^a	1.745 ^b	2.396 ^a	4.183 ^a	−6.855 ^a	−0.624 ^c	−0.695	0.203	1.492 ^b	2.039 ^b	2.083 ^c
Taiwan	6.112 ^a	0.191	−0.059	−0.199	−0.607	−1.066 ^b	−1.555 ^b	−6.459 ^a	0.483 ^b	−0.056	−0.254	−0.508	−0.964 ^c	−1.342 ^c
Thailand	6.514 ^a	0.380	0.215	0.743	0.487	0.299	0.716	−6.566 ^a	−0.595 ^c	−0.258	−0.242	−0.124	−0.272	−0.120
<i>Panel E: Positive shocks of $s_t^+ \geq +10\%$</i>								<i>Panel F: Negative shocks of $s_t^- \leq -10\%$</i>						
Hong Kong	12.573 ^a	0.701	1.387	3.456 ^a	3.611 ^a	4.172 ^a	1.638	−11.687 ^a	3.901 ^a	6.597 ^a	5.721 ^a	7.576 ^a	0.641	−10.332 ^a
India	14.333 ^a	4.453 ^a	4.394 ^a	4.825 ^b	9.198 ^a	10.731 ^a	3.896	−11.169 ^a	8.358 ^a	9.245 ^a	8.661 ^a	9.502 ^a	13.738 ^a	4.607
Indonesia	12.251 ^a	1.834 ^a	5.782 ^a	6.886 ^a	7.553 ^a	7.065 ^a	1.72	−14.419 ^a	−1.517 ^b	−0.394	3.808 ^a	6.716 ^a	5.527 ^a	2.170
Korea	9.987 ^a	−0.153	−0.931	−6.832 ^b	−6.19 ^b	−10.385 ^a	−10.681 ^b	−13.580 ^a	2.544 ^a	2.513 ^b	1.902	1.771	−0.427	−2.518
Malaysia	13.143 ^a	−1.225 ^c	0.912	2.629 ^b	−6.004 ^a	−1.969	−4.611 ^b	−12.674 ^a	1.912 ^a	2.999 ^a	7.390 ^a	8.900 ^a	3.348 ^b	3.600 ^c
Pakistan	12.702 ^a	−0.336	2.495	2.433	1.235	−3.971	−1.902	−13.280 ^a	2.218	14.923 ^a	14.591 ^a	17.426 ^a	17.368 ^a	9.961 ^b
Philippines	14.075 ^a	−1.066	−2.646 ^b	−1.780	−2.004	−4.177 ^b	−3.029	−	−	−	−	−	−	−
Singapore	15.156 ^a	−8.186 ^a	−11.397 ^a	−11.432 ^a	−13.878 ^a	−15.517 ^a	−16.611 ^a	−11.719 ^a	−6.832 ^a	−6.837 ^a	−1.003	−6.194 ^a	−7.857 ^a	−12.398 ^a
Taiwan	14.041 ^a	−6.768 ^a	−1.253	−1.506	−1.749	−1.243	1.066	−11.626 ^a	2.480 ^a	6.437 ^a	2.835 ^c	7.742 ^a	6.642 ^a	8.828 ^a
Thailand	10.682 ^a	−1.866 ^b	−0.685	−4.212 ^a	−5.053 ^a	−5.013 ^b	3.837	−11.870 ^a	5.338 ^a	6.761 ^a	6.195 ^c	4.339	4.303	0.730

^a, ^b and ^c respectively denote statistical significance at a 1-, 5- and 10-percent level. Statistical significance is determined using the standard *t*-statistic. s_t^+ and s_t^- respectively denote the magnitude of positive and negative shocks at time *t*. The CARs are estimated using a dummy variable method similar to that of Karafiath (1988). The CARs are estimated over a window of ten days. To conserve space, we present the results at selected intervals. The values of the CARs are in percentages.

$-3\% > s_t^- > -5\%$ are followed by negative and significant CARs (see panels A and B). The CARs are significant for up to day ten in some cases, but the price adjustment appears somewhat quicker following negative shocks. These results support return continuations in line with those of Lasfer et al. (2003). The CARs following positive and negative shocks are not significant for India, Pakistan and Taiwan. Also, the CARs following positive shocks are not significant for Korea. Thus some stock markets appear efficient following small price shocks. There is however some evidence of overreaction following negative price shocks in the case of the Korean index.

The results in panels C and D (of Table 2), for the most part, support both return continuations and market efficiency. Here, the positive and negative shocks are within the ranges of $+5\% \leq s_t^+ < +10\%$ and $-5\% \geq s_t^- > -10\%$, respectively. The support for return continuations and market efficiency is almost as strong as for earlier results, but return continuations still dominate. The support for both hypotheses does not always hold for the same stock market, given the sign of the shock. The price adjustment is much quicker following negative shocks compared with positive shock. As before, there is limited evidence of overreaction, and here the overreaction hypothesis holds following positive and negative shocks for the Pakistani and Taiwanese indexes, respectively.

The CARs following price shocks of $s_t^+ \geq +10\%$ and $s_t^- \leq -10\%$ provide the strongest support of overreaction (see panels E and F of Table 2). Specifically, the day one CARs following the positive (negative) shocks are negative (positive) and significant for four (six) indexes. The remaining day-one CARs are not significant. Thus there is mixed support for both market efficiency and overreaction following positive shocks, whilst overreaction dominates following negative shocks. In some cases, these CARs are significant for up to day ten.

Our OLS results therefore support return continuations, overreaction and market efficiency. The specific result depends on the magnitude of the price shock and the index under consideration. We find support for return continuations following small price shocks as well as for intermediate levels of price shocks. Return continuations can follow small price shocks, if investors are unwilling to forego the transaction costs associated with rebalancing their portfolios. The overreaction hypothesis holds following the largest negative price shocks, whilst the results are mixed for the largest positive price shocks. Prior studies (see e.g., Bremer and Sweeney, 1991) also support overreaction at and above those trigger values for individual stocks. As such, large trigger values appear to be associated with overreaction and/or market efficiency. If stock markets respond more strongly to big news than to small news, the price reaction following big news appears to give rise to price reversals that can last several days, depending on the stock market. Also, in efficient markets, prices should adjust quickly in the aftermath of unanticipated positive or negative information releases. We find support for this view for a large minority of indexes.

4.3. GARCH estimates

We now consider the GARCH-based results. Overall, we find that the symmetric GARCH and GJR-GARCH results are quantitatively similar – a finding consistent with those of Ajayi et al. (2006).¹⁰ Even if Engle and Ng (1993) show that the symmetric GARCH tends to overestimate conditional volatility relative to the GJR-GARCH method, this potential weakness of the symmetric GARCH appears to have little effect on the CARs and their volatility.¹¹ Given the similarity in the two sets of results, we prefer to focus on the GJR-GARCH results since by so doing we allow for any asymmetric volatility that may affect the ARs. We present those results below.

4.3.1. Positive and negative shocks under the GJR-GARCH method

Table 3 presents the results for the GJR-GARCH method. Positive shocks within the range of $+3\% < s_t^+ < +5\%$ are followed by positive and significant day one CARs for all stock indexes, except India, Pakistan and Taiwan (see Panel A). Here, support for return continuations is slightly stronger compared with the OLS results for shocks of this magnitude. For some indexes, the CARs are also significant for up to day ten.

¹⁰ Specifically, only the ten-day CARs of the symmetric GARCH and GJR-GARCH methods are statistically different and this is following positive shocks of more than 10%.

¹¹ Most financial economists also agree that market returns contain negative asymmetry that affects stock returns but such negative asymmetries do not seem to impact on our ARs in a substantial way. The explanations for the negative asymmetries include: the leverage effect of Black (1976) and Christie (1982); volatility clustering of Engle et al. (1990); and, the volatility feedback mechanism of Pindyck (1984) and French et al. (1987).

Table 3

GJR-GARCH(1,1) estimates of CARs following positive and negative shocks.

Country	Mean AR	CAR1	CAR2	CAR3	CAR4	CAR5	CAR10	Mean AR	CAR1	CAR2	CAR3	CAR4	CAR5	CAR10
<i>Panel A: Positive shocks of $+3\% < s_t^+ < +5\%$</i>								<i>Panel B: Negative shocks of $-3\% > s_t^- > -5\%$</i>						
Hong Kong	3.544 ^a	0.370 ^b	0.494 ^b	0.608 ^b	0.899 ^a	0.810 ^b	1.178 ^b	-3.794 ^a	-0.099	-0.170	-0.201	-0.057	0.123	0.002
India	3.629 ^a	-0.217	-0.276	0.037	0.305	0.857 ^c	0.790	-3.716 ^a	0.003	-0.247	-0.328	-0.359	-0.237	-1.652 ^a
Indonesia	3.617 ^a	0.956 ^a	1.031 ^a	0.467	0.397	0.325	0.683	-3.548 ^a	-0.480 ^b	-0.968 ^a	0.104	-0.905 ^b	-0.942 ^c	-2.218 ^a
Korea	3.656 ^a	0.263 ^c	0.284	-0.037	-0.130	-0.123	-0.594	-3.731 ^a	0.300 ^c	0.558 ^b	0.490 ^c	0.500	0.527	0.594
Malaysia	3.345 ^a	0.468 ^a	0.627 ^a	0.457	0.479	0.096	0.225	-3.545 ^a	-0.471 ^b	-0.362	-0.327	-0.151	0.079	1.015
Pakistan	3.692 ^a	0.028	-0.001	0.115	0.160	0.267	1.423 ^b	-3.668 ^a	0.067	0.076	0.151	0.145	0.066	0.570
Philippines	3.571 ^a	0.529 ^a	0.600 ^b	0.885 ^a	1.021 ^b	0.600	0.940	-3.805 ^a	-0.291	-0.619 ^c	-0.72 ^c	-0.933 ^c	-0.567	-0.268
Singapore	3.601 ^a	0.961 ^a	1.052 ^a	0.763 ^b	0.975 ^b	0.858 ^c	0.243	-3.718 ^b	-0.145	-0.407	-0.375	-0.266	0.179	1.585
Taiwan	3.690 ^a	-0.009	0.218	0.202	0.131	0.435	0.640	-3.741 ^a	0.239 ^c	-0.039	-0.291	-0.512 ^c	-0.461	0.190
Thailand	3.605 ^a	0.747 ^a	1.172 ^a	1.011 ^a	0.891 ^b	0.869 ^b	1.253 ^b	-3.751 ^a	-0.290	-0.847 ^a	-0.878 ^b	-0.350	-0.600	-0.357
<i>Panel C: Positive shocks of $+5\% \leq s_t^+ < +10\%$</i>								<i>Panel D: Negative shocks of $-5\% \geq s_t^- > -10\%$</i>						
Hong Kong	6.037 ^a	-0.069	0.386	1.260 ^c	0.968	0.465	0.040	-6.581 ^a	0.022	-0.317	-0.402	-1.111	-1.016	-0.582
India	6.757 ^a	0.361	0.471	0.059	-0.925	-0.624	0.071	-6.558 ^a	-0.467	0.540	0.597	-0.187	-0.260	-1.673
Indonesia	6.705 ^b	2.494 ^b	3.036 ^a	2.667 ^b	1.490	1.290	2.398	-6.051 ^a	1.833 ^a	2.853 ^a	2.821 ^a	2.733 ^a	1.887 ^c	4.853 ^a
Korea	6.071 ^a	1.016 ^b	0.954 ^b	0.787	0.669	0.651	1.280	-6.553 ^a	0.550 ^a	0.956 ^a	1.898 ^a	2.145 ^a	1.960 ^a	1.436 ^c
Malaysia	5.625 ^a	0.604	0.024	0.551	-0.504	-0.812	0.183	-6.017 ^a	0.544	1.735 ^a	2.918 ^a	3.324 ^a	2.980 ^a	1.937
Pakistan	6.346 ^a	-1.544 ^a	-1.850 ^a	-1.157	-0.551	-0.784	-1.290	-7.232 ^a	0.151	0.825	-0.156	-0.095	0.122	1.062
Philippines	6.212 ^a	0.936 ^c	-0.319	-0.480	-0.317	-0.051	3.365 ^c	-6.908 ^a	-0.632	-0.369	0.351	0.239	0.427	-0.465
Singapore	5.754 ^a	0.805	1.146	1.095	-0.463	0.086	3.583	-6.652 ^a	0.066	1.803 ^b	2.691 ^b	2.785 ^b	4.317 ^a	4.827 ^b
Taiwan	6.020 ^a	0.199	0.161	0.104	-0.080	-0.439	-0.201	-6.434 ^a	0.869 ^a	0.904 ^b	0.897 ^c	1.004	0.799	1.053
Thailand	6.312 ^a	0.565	0.073	0.254	-0.223	-0.625	-0.455	-6.106 ^a	0.238	0.617	0.295	0.751	0.839	1.257
<i>Panel E: Positive shocks of $s_t^+ \geq +10\%$</i>								<i>Panel F: Negative shocks of $s_t^- \leq -10\%$</i>						
Hong Kong	12.411 ^a	0.294	-0.563	1.078	1.209	1.799	12.411 ^a	-11.189	4.862 ^c	10.555 ^a	10.801 ^b	12.403 ^b	2.528	-13.709 ^c
India	14.932 ^a	4.323	4.405	5.011	10.7	12.69	14.932 ^a	-11.307	8.231	6.995 ^a	5.273 ^b	6.828	13.113 ^a	-8.412 ^c
Indonesia	11.597 ^a	-1.594 ^a	-5.398 ^a	-3.927 ^a	-7.403 ^a	-7.327 ^a	11.597 ^a	-13.137 ^a	-0.213	3.736 ^a	8.178	2.204	0.047	5.255
Korea	9.970 ^a	-0.168 ^a	-1.032	-8.280	-6.598	-11.402	9.970 ^a	-15.308 ^a	3.371 ^a	1.748	1.616	3.888 ^b	1.387	-0.647
Malaysia	14.982 ^a	-0.162	0.894	-2.082	-8.665 ^b	-4.089	14.982 ^a	-11.753	2.250	0.453	1.416	2.319	3.230	-6.217 ^c
Pakistan	12.743	-0.301	3.940	0.271	-9.189	12.743	-12.743	-13.239	2.257	18.021 ^a	15.351 ^b	18.484 ^b	17.637	5.012
Philippines	14.540 ^a	-1.100	-0.020	0.000	0.00	-0.014 ^b	14.540 ^a	-	-	-	-	-	-	-
Singapore	14.857	-3.347	-4.892	-0.407	0.149	-6.554	14.857	-7.343 ^b	0.398	-0.542	1.464	-1.749	-0.938	-12.058 ^b
Taiwan	12.829 ^a	-6.708 ^a	-2.510 ^b	-2.988	-0.394	-2.373	12.829 ^a	-11.879	7.231 ^a	9.152 ^a	7.991 ^a	11.174 ^a	11.055 ^a	11.569 ^a
Thailand	10.895 ^b	-1.691	-0.721	-6.154 ^b	-6.738 ^c	-6.454	10.895 ^b	-11.913	5.294	4.194	1.764	-1.607	0.698	4.627

^a, ^b and ^c respectively denote statistical significance at a 1-, 5- and 10-percent level. Statistical significance is determined using the standard *t*-statistic. s_t^+ and s_t^- respectively denote the magnitude of positive and negative shocks at time *t*. The CARs are estimated using a dummy variable method similar to that of Karafiath (1988) but based on the GJR-GARCH estimation method. The CARs are estimated over a window of ten days. To conserve space, we present the results at selected intervals. The values of the CARs are in percentages.

Negative shocks within the range of $-3\% > s_t^- > -5\%$ (see Table 3, Panel B) are followed by negative (positive) and significant day one CARs for the Indonesian and Malaysian (Korean and Taiwanese) indexes. The CARs are significant for up to three days after the shock so the price adjustment is much quicker relative to the OLS results at similar trigger values. As such the evidence provides greater support for market efficiency under the GJR-GARCH method.

Panel C of Table 3 shows that positive shocks within the range of $+5\% \leq s_t^+ < +10\%$ are followed by positive (negative) and significant CARs for Indonesia, Korea and the Philippines (Pakistan). Those CARs are not significant beyond day three. Overall, the CARs are not significant for the majority of indexes and where significant, the price adjustment is quicker relative to smaller price shocks. Similarly, negative shocks within the range of $-5\% > s_t^- > -10\%$ are followed by positive and significant CARs for Indonesia, Korea and Taiwan. This result supports overreaction. However, the price adjustment for most of the markets appears to follow the efficient market hypothesis.

Compared to earlier results, the results in Panel E and F of Table 3 provide the strongest support for market efficiency. Here, the one-day CARs following positive shocks of $s_t^+ \geq +10\%$ and negative shocks of $s_t^- \leq -10\%$ are not significant, except in six cases. These cases provide support of overreaction. In general, the use of large trigger values relative to small trigger values leads to important differences in the results under the GJR-GARCH method. Specifically, all support for return continuations disappear when the trigger values are as large as $s_t^+ \geq +10\%$ and $s_t^- \leq -10\%$. Furthermore, market efficiency dominates at trigger values larger than 10% in absolute value, and there is some limited support for the overreaction hypothesis at trigger values larger than 10% in absolute value.

Overall, our results point to substantial differences in the behavior of the CARs given the magnitude of the trigger value and the estimation method. Return continuations are followed by positive and negative shocks within the ranges of $+3\% < s_t^+ < +5\%$ and $-3\% > s_t^- > -5\%$ respectively. However, the degree of return continuations is stronger under the OLS method compared with the GJR-GARCH method, particularly following positive shocks. Larger trigger values are followed mainly by market efficiency under the GJR-GARCH method. Furthermore, market efficiency still dominates at $s_t^+ \geq +10\%$ or $s_t^- \leq -10\%$ (under the GJR-GARCH) and although there is some limited support for overreaction, all trace of return continuations disappears. Under the OLS method, positive shocks of $s_t^+ \geq +10\%$ are followed by a mix of overreaction and market efficiency, whilst overreaction mainly follows negative shocks of $s_t^- \leq -10\%$. Furthermore, at these trigger values there is also evidence of return continuations although to a very limited extent. We attribute the differences in the OLS and GJR-GARCH results to the ability of the GJR-GARCH method in improving estimation efficiency.¹²

4.3.2. Volatility changes under the GJR-GARCH

We now consider the effects of price shocks on the change in conditional volatility. The GJR-GARCH estimates in Table 4 show that except for shock sizes of $s_t^+ \geq +10\%$ and $s_t^- \leq -10\%$, the mean changes in abnormal volatility on day zero are typically positive and significant. At day zero, shock sizes of $s_t^+ \geq +10\%$ and $s_t^- \leq -10\%$ are however followed by a mix of positive and negative mean changes in abnormal volatility. Here, the mean changes in volatility appear less predictable.

The table also shows that the changes in abnormal volatility following the event day vary according to the sign of the price shock. In general, there is a tendency for the day one abnormal volatility to be significant, irrespective of the size of the shock. Positive shocks within the range of $+3\% < s_t^+ < +5\%$ (see Panel A, Table 4) are followed by volatility coefficients that are significant for up to day ten in most cases. Whilst most of the significant day one coefficients are negative, all significant day one coefficients decline in magnitude over time. That is, the post-event volatility changes decrease after day zero to become smaller or negative but they largely remain significant over the ten-day window. This finding is not consistent with the UIH.

The day one volatility coefficients following negative shocks within the range $-3\% < s_t^- < -5\%$, are positive and significant for seven indexes. This contrasts with the sign of the coefficients following positive shocks of similar magnitudes. As before, the post-event coefficients become smaller or negative over time; only a few remain significant at day ten.

¹² To facilitate a comparison with the period covered by the Lasfer et al. (2003), we repeat the analysis over the period 1989–1998, using the GJR-GARCH method. The results for 1989–1998 are generally in line with those reported here. With very few exceptions, we find support for the EMH for the majority of the indexes, particularly following larger price shocks.

Table 4

GJR-GARCH(1,1) estimates of the volatility of the ARs following positive and negative shocks.

Country	Day 0	Day1	Day[1,2]	Day[1,3]	Day[1,4]	Day[1,5]	Day[1,10]	Day 0	Day1	Day[1,2]	Day[1,3]	Day[1,4]	Day[1,5]	Day[1,10]
<i>Panel A: Positive shocks of $+3\% < s_t^+ < +5\%$</i>								<i>Panel B: Negative shocks of $-3\% < s_t^- < -5\%$</i>						
Hong Kong	0.498 ^a	−0.798 ^a	−0.413 ^a	−0.235 ^a	−0.155 ^a	−0.103 ^a	−0.021	2.007 ^a	0.383 ^b	0.064	0.006	−0.028	−0.039	−0.011
India	1.184 ^a	0.501 ^a	0.283 ^a	0.222 ^a	0.174 ^a	0.148 ^a	0.098 ^a	1.426 ^a	0.704 ^a	0.339 ^a	0.226 ^a	0.174 ^a	0.151 ^a	0.075 ^a
Indonesia	1.188 ^a	0.268 ^a	0.073 ^c	−0.052 ^c	−0.099 ^a	−0.100 ^a	−0.045 ^a	0.918 ^a	−0.142	−0.089	−1.242 ^a	−0.073 ^b	−0.058 ^b	−0.036 ^b
Korea	0.360 ^a	0.053	−0.002	−0.003	−0.007	−0.006	−0.009 ^c	0.604 ^a	0.280 ^a	0.125 ^a	0.073 ^a	0.047 ^a	0.030 ^b	0.002
Malaysia	−1.426 ^a	−1.088 ^a	−0.550 ^a	−0.357 ^a	−0.237 ^a	−0.176 ^a	−0.070 ^a	1.598 ^a	0.363 ^c	0.128	−0.006	−0.054	−0.070 ^c	−0.057 ^a
Pakistan	0.786 ^a	−0.811 ^a	−0.403 ^a	−0.268 ^a	−0.182 ^a	−0.154 ^a	−0.076 ^a	1.357 ^a	−0.535 ^b	−0.249 ^b	−0.170 ^b	−0.177 ^a	−0.150 ^a	−0.066 ^a
Philippines	0.904 ^a	−0.172	−0.134	−0.173 ^b	−0.145 ^a	−0.098 ^b	−0.018	2.419 ^a	0.922 ^a	0.509 ^a	0.343 ^a	0.277 ^a	0.246 ^a	0.102 ^a
Singapore	0.558 ^a	−1.392 ^a	−0.800 ^a	−0.496 ^a	−0.373 ^a	−0.271 ^a	−0.080 ^a	2.345 ^a	1.102 ^b	0.590 ^a	0.340 ^b	0.253 ^b	0.177 ^b	0.058 ^c
Taiwan	0.590 ^a	−0.277 ^a	−0.088 ^c	−0.052	−0.022	−0.015	−0.010	1.078 ^a	0.145	0.066	0.024	−0.005	−0.021	−0.034 ^a
Thailand	0.796 ^a	−0.443 ^a	−0.234 ^a	−0.115 ^b	−0.092 ^a	−0.071 ^a	−0.072 ^a	2.341 ^a	1.019 ^a	0.430 ^a	0.245 ^a	0.154 ^b	0.101 ^c	−0.024
<i>Panel C: Positive shocks of $+5\% \leq s_t^+ < +10\%$</i>								<i>Panel D: Negative shocks of $-5\% \geq s_t^- > -10\%$</i>						
Hong Kong	−0.275	−3.815 ^a	−1.765 ^a	−1.184 ^a	−0.827 ^a	−0.602 ^a	−0.243 ^a	5.838 ^a	1.730 ^b	0.771 ^b	0.408 ^c	0.187	0.079	−0.142 ^b
India	2.544 ^a	0.568 ^c	0.334 ^b	0.288 ^a	0.259 ^a	0.238 ^a	0.190 ^a	3.961 ^a	0.774	−0.089	−0.21	−0.209 ^c	−0.168 ^c	−0.166 ^a
Indonesia	12.098 ^a	5.918 ^a	3.203 ^a	2.284 ^a	1.762 ^a	1.399 ^a	0.635 ^a	2.127 ^a	−1.618 ^a	−1.135 ^a	−0.827 ^a	−0.624 ^a	−0.461 ^a	−0.282 ^a
Korea	0.442 ^a	−0.490 ^a	−0.226 ^a	−0.187 ^a	−0.167 ^a	−0.147 ^a	−0.112 ^a	1.297 ^a	−0.614 ^a	−0.574 ^a	−0.419 ^a	−0.330 ^a	−0.280 ^a	−0.150 ^a
Malaysia	0.300	−2.483 ^a	−1.232 ^a	−0.749 ^a	−0.595 ^a	−0.475 ^a	−0.167 ^a	2.608 ^a	−0.887	−0.689 ^a	−0.676 ^a	−0.607 ^a	−0.460 ^a	−0.195 ^a
Pakistan	2.187 ^a	−3.245 ^a	−2.244 ^a	−1.507 ^a	−1.048 ^a	−0.877 ^a	−0.322 ^a	3.857 ^a	−1.721	−1.188 ^b	−0.641 ^b	−0.700 ^a	−0.661 ^a	−0.372 ^a
Philippines	4.611 ^a	1.236 ^c	0.154	−0.162	−0.184	−0.204	−0.055	7.632 ^a	3.435 ^a	1.774 ^a	1.212 ^a	0.836 ^a	0.567 ^a	0.057
Singapore	2.331 ^b	−2.996 ^b	−1.657 ^a	−0.853 ^a	−0.585 ^c	−0.402	−0.188 ^c	3.271 ^a	−3.646 ^a	−2.077 ^a	−1.387 ^a	−1.004 ^a	−0.789 ^a	−0.333 ^a
Taiwan	1.096 ^a	−1.421 ^a	−0.583 ^a	−0.383 ^a	−0.252 ^a	−0.169 ^a	−0.044 ^c	2.471 ^a	−0.203	−0.183	−0.251 ^b	−0.227 ^a	−0.172 ^a	−0.064 ^b
Thailand	2.236 ^a	−1.497 ^a	−0.792 ^a	−0.571 ^a	−0.557 ^a	−0.525 ^a	−0.254 ^a	3.249 ^a	−1.071 ^c	−1.035 ^a	−0.749 ^a	−0.583 ^a	−0.428 ^a	−0.190 ^a
<i>Panel E: Positive shocks of $s_t^+ \geq +10\%$</i>								<i>Panel F: Negative shocks of $s_t^- \leq -10\%$</i>						
Hong Kong	−5.282 ^a	−12.694 ^a	−5.865 ^a	−3.400 ^a	−2.399 ^a	−1.939 ^a	−0.999 ^a	59.505 ^a	44.593 ^a	18.711 ^a	12.486 ^a	9.117 ^a	8.261 ^a	4.034 ^a
India	8.146 ^b	2.232	1.575	1.267	0.535	0.440	0.649	1.681	−11.263 ^a	−5.886 ^a	−4.188 ^a	−3.076 ^a	−2.429 ^a	−1.422 ^a
Indonesia	1.223 ^a	−5.277 ^a	−5.034 ^a	−8.213 ^a	−2.247 ^a	−1.695 ^a	−0.516 ^a	−2.690 ^a	−114.80 ^a	−57.400 ^a	−43.00 ^a	−30.700 ^a	−24.900 ^a	−9.850 ^a
Korea	−1.690 ^a	−4.902	−2.236	−1.817 ^a	−1.252	−1.140 ^a	−0.517 ^a	1.288	−6.399 ^a	−3.298 ^a	−2.409 ^a	−1.908 ^a	−1.540 ^a	−0.757 ^a
Malaysia	7.085	−10.170 ^a	−7.966 ^a	−5.740 ^a	−5.525 ^a	−3.847 ^a	−1.426 ^a	18.995 ^a	−2.191	−5.786 ^a	−4.115 ^a	−3.204 ^a	−2.459 ^a	−1.080 ^a
Pakistan	−21.786 ^b	−40.508 ^a	−17.916 ^a	−10.198 ^a	−6.475 ^b	−5.357 ^a	−1.429	25.603	0.875	−13.916 ^b	−6.613	−6.305 ^c	−4.447	−1.485
Philippines	2.660	−19.280 ^a	−6.720 ^a	−5.060 ^a	−2.960 ^a	−2.240 ^a	−0.965 ^a	−	−	−	−	−	−	−
Singapore	−1.234	−34.509 ^a	−15.257 ^a	−9.252 ^a	−6.361 ^a	−5.045 ^a	−1.794 ^a	27.683 ^a	−1.595	−7.497 ^a	−5.035 ^a	−3.761 ^a	−2.591 ^a	−0.988 ^a
Taiwan	6.829 ^a	−10.824 ^a	−6.969 ^a	−4.979 ^a	−2.985 ^a	−2.604 ^a	−0.995 ^a	16.266 ^a	1.343	0.144	−0.307	−1.631 ^a	−1.972 ^a	−1.399 ^a
Thailand	−0.161	−10.704 ^a	−4.580 ^a	−3.826 ^a	−2.871 ^a	−2.002 ^a	−0.477 ^b	−25.196 ^a	−38.534 ^a	−18.286 ^a	−11.611 ^a	−8.322 ^a	−6.076 ^a	−2.816 ^a

^a, ^b and ^c respectively denote statistical significance at a 1-, 5- and 10-percent level. Statistical significance is determined using the standard *t*-statistic. s_t^+ and s_t^- respectively denote the magnitude of positive and negative shocks at time *t*. The volatility coefficients are estimated using a dummy variable method similar to that of Karafiath (1988) but based on the GJR-GARCH estimation method. The estimates are over a window of ten days and corresponding to the CAR estimates in Table 3. To conserve space, we present the results at selected intervals. Day[1] denotes the change in volatility for day one whilst Day[1,2] denotes the change in volatility across days one and two. The volatility coefficients are multiplied by 10⁴.

Most of the day one volatility coefficients following positive shocks within the range of $+5\% \leq s_t^+ < +10\%$ are negative and significant. This result is in line with those following positive shocks of $+3\% < s_t^+ < +5\%$. The day one volatility coefficients following negative shocks within $-5\% \leq s_t^- < -10\%$ are negative and significant in four cases; a further two are positive and significant at day one. So the change in volatility appears quicker for negative shocks of this magnitude.

Positive shocks of $s_t^+ \geq 10\%$ and negative shocks of $s_t^- \leq -10\%$ are also followed by significant day one volatility coefficients. Eight indexes exhibit negative and significant day one coefficients following positive shocks of $s_t^+ \geq 10\%$, whilst four indexes exhibit significant and negative day one volatility coefficients following negative shocks of $s_t^- \leq -10\%$. Overall, it appears that the post-event volatility changes are negative irrespective of the sign of shock.

Three further features are worth noting in relation to the CARs and their volatility estimates. These features are common across the indexes and shock sizes. Firstly, the day one volatility coefficients can be significant even if the corresponding CARs are insignificant. For example, for shock sizes of $+3\% < s_t^+ < +5\%$, the day one CARs for India, Pakistan and Taiwan (see Table 3, Panel A) are not significant even if the corresponding day one volatility coefficients are significant (see, Table 4, Panel A).¹³ So volatility changes can be significant even if the associated CARs are effectively zero.¹⁴ Secondly, the post-event CARs can be significant even if the associated volatility coefficients are insignificant. The Philippines index is a case in point (see Panel A in both Tables 3 and 4). Finally, the post-event volatility coefficients can be negative and significant even if the corresponding CARs are positive, as in the case of Hong Kong, Malaysia, Singapore and Thailand (see Panel A each in Tables 3 and 4). Overall, we do not find a consistent relationship between the CARs and the changes in volatility. This finding might reflect microstructure effects. As indicated earlier, Brown et al.'s (1988) results for volatility changes are based on the volatility of returns over both the pre- and post-event periods. Our use of the GJR-GARCH method to capture changes in conditional volatility would appear to be a more direct test.

4.4. The Asian financial crisis

Pesenti and Tille (2000) indicate that following the years of stellar performance, many Asian countries such as Thailand, Malaysia and Indonesia experienced substantial falls in both stock prices and their currency. Empirical studies also show that the Asian financial crisis of 1997 affected the betas of many firms. Specifically, Maroney et al. (2004) show that after the start of the 1997 Asian financial crisis, the national equity betas of Asian markets increased whilst average equity returns decreased. These results suggest that the Asian financial crisis may have had important impacts on both the CAR and volatility estimates in our study. To test this hypothesis, we split the sample into two periods using the cut-off point of June 30, 1997. We then estimate the ARs and volatility for both periods using the GJR-GARCH method. Those estimates are for up to ten days but to save space, we show the CAR and volatility estimates for up to day two.

4.4.1. CAR estimates

Table 5 shows the CARs for the pre- and post-crisis periods. For the pre-crisis period, support for return continuations is strongest following positive shocks within the range $+3\% < s_t^+ < +5\%$. However, there is equal support for both return continuations and market efficiency at this trigger value. Negative shocks within $-3\% > s_t^- > -5\%$ are mainly followed by insignificant day one CARs, in support of market efficiency. The support for market efficiency increases as the shock size increases. Support for overreaction is strongest following negative shocks within the range $-5\% \leq s_t^- < -10\%$. Even so, only four indexes exhibit positive and significant day one CARs for such shocks. In brief, the results suggest that the markets are generally efficient for the pre-crisis period, although a minority of the CARs can remain significant for more than one day.

The post-crisis period results are broadly similar to those of the pre-crisis period. However, the evidence in support of market efficiency is stronger following negative shocks within $-3\% > s_t^- > -5\%$, and positive shocks of $s_t^- \leq -10\%$. For all shock sizes, the price adjustment is quicker compared to the pre-crisis period.

¹³ Recall that irrespective of the trigger value, the day one volatility coefficients are generally significant and this tendency is stronger the smaller the trigger value.

¹⁴ Brown et al. (1988, p. 364) note: "... although the UIH predicts that risk will increase following an informational shock, there is no a priori reason to conclude that the change will be permanent."

Table 5

GJR-GARCH estimates of CARs following positive and negative shocks over the pre- and post-Asian crisis periods.

Country	Panel A: Pre-crisis period						Panel B: Post-crisis period					
	Mean AR	CAR1	CAR2	Mean AR	CAR1	CAR2	Mean AR	CAR1	CAR2	Mean AR	CAR1	CAR2
	Positive shocks of $+3\% < s_t^+ < +5\%$			Negative shocks of $-3\% > s_t^- > -5\%$			Positive shocks of $+3\% < s_t^+ < +5\%$			Negative shocks of $-3\% > s_t^- > -5\%$		
Hong Kong	3.531 ^a	0.365 ^c	0.522 ^c	−3.694 ^a	−0.309 ^c	−0.401	3.734 ^a	0.057	0.303	−3.862 ^b	0.293	0.242
India	3.647 ^a	0.271	0.500	−3.650 ^a	−0.553	−0.600	3.592 ^a	−0.557 ^b	−0.834 ^b	−3.799 ^a	0.285	−0.166
Indonesia	3.291 ^c	3.302 ^a	3.074 ^a	−3.584 ^a	−0.287	−1.029 ^a	3.552 ^a	0.405 ^c	0.490	−3.643 ^a	−0.498	−0.691
Korea	3.608 ^a	0.204	0.137	−3.666 ^a	0.415 ^a	0.538 ^a	3.773 ^a	0.343	0.502	−3.821 ^a	0.169	0.551
Malaysia	3.376 ^a	0.616 ^a	0.859 ^a	−3.428 ^a	−0.258	−0.104	3.191 ^a	0.084	0.024	−3.717 ^b	−0.789 ^b	−0.851 ^c
Pakistan	3.777 ^a	0.463	1.016 ^a	−3.567 ^a	−0.017	0.383	3.782 ^a	−0.196	−0.645	−3.805 ^a	0.045	−0.310
Philippines	3.600 ^a	0.236	0.653 ^c	−3.977 ^a	−0.376	−1.225 ^b	3.427 ^a	0.779 ^a	0.545	−3.634 ^a	−0.248	−0.244
Singapore	3.577 ^a	0.768 ^b	0.915 ^a	−3.483	−0.673	−0.634	3.801 ^a	1.069 ^a	0.959 ^b	−3.673 ^b	−0.213	−0.439
Taiwan	3.712 ^a	−0.028	0.300	−3.774 ^a	0.446 ^a	0.017	3.686 ^a	0.057	−0.016	−3.546 ^a	−0.324	−0.452
Thailand	3.560 ^a	1.027 ^a	1.270 ^a	−3.813 ^a	−0.566 ^c	−0.995 ^b	3.723 ^a	0.474 ^c	1.180a	−3.573 ^a	−0.207	−0.917 ^b
	Positive shocks of $+5\% \leq s_t^+ < +10\%$			Negative shocks of $-5\% \geq s_t^- > -10\%$			Positive shocks of $+5\% \leq s_t^+ < +10\%$			Negative shocks of $-5\% \geq s_t^- > -10\%$		
Hong Kong	5.737 ^a	−0.283	0.190	−6.351 ^a	0.258	−0.657	6.241 ^a	0.960	0.509	−7.082 ^a	−1.903 ^b	−0.484
India	7.085 ^a	−0.106	0.503	−6.597 ^a	−0.361	−0.431	7.020 ^a	0.393	0.156	−6.519 ^b	−0.497	0.907
Indonesia	7.088	2.999	2.739 ^a	−5.210	4.794 ^a	6.704 ^a	6.090 ^c	1.016	2.711 ^b	−6.279 ^a	0.992 ^c	2.121 ^b
Korea	5.880 ^a	1.049 ^a	0.702	−6.790 ^a	1.596 ^a	1.565 ^a	6.315 ^a	0.868	0.985	−6.153 ^a	−1.094 ^b	−1.108
Malaysia	5.396 ^a	−0.004	−0.728	−6.113 ^a	0.086	1.703 ^c	6.867	3.376 ^b	2.972 ^c	−5.706 ^a	0.887	0.930
Pakistan	6.786 ^c	−2.505 ^c	−2.811	−5.327	−0.848	3.595 ^b	6.196 ^a	−1.253 ^b	−1.780 ^b	−7.605 ^a	0.289	−0.133
Philippines	6.257 ^c	1.056	0.842	−7.311 ^a	−0.875	0.460	6.166 ^a	0.387	−1.412	−6.213 ^b	−0.226	−0.738
Singapore	5.495	1.435	2.458	−6.129	−0.090	1.126	6.237 ^a	0.709	1.631	−7.158 ^a	−0.351	1.923 ^b
Taiwan	6.303 ^a	0.009	−0.243	−6.470 ^a	1.025 ^a	0.750	5.199 ^a	0.805	1.079	−6.167 ^b	0.007	0.531
Thailand	6.381 ^a	0.603	−0.425	−5.850 ^a	1.643 ^a	1.974 ^a	6.333 ^a	0.495	0.692	−6.180 ^a	−0.928 ^b	−1.174
	Positive shocks of $s_t^+ \geq +10\%$			Negative shocks of $s_t^- \leq -10\%$			Positive shocks of $s_t^+ \geq +10\%$			Negative shocks of $s_t^- \leq -10\%$		
Hong Kong	11.254	0.883	0.669	−11.428	4.722	13.870 ^a	13.447 ^a	−1.219	−4.165	−11.014	6.643	1.072
India	14.918 ^a	4.379	4.519	−10.328	8.917	5.986 ^a	−	−	−	−12.019	7.771	8.265
Indonesia	15.855 ^a	0.700	−5.176 ^a	−13.373 ^a	−0.169	0.464	10.903 ^a	0.131	−1.326	−10.800	1.472	7.403 ^c
Korea	−	−	−	−17.407	2.469	5.171	9.988	−0.148	−0.976	−12.482	3.840 ^b	0.241
Malaysia	11.000	−10.229	−19.655	−11.386	0.763	−1.579	15.270 ^a	1.128	3.082	−12.312	6.585	10.366
Pakistan	−	−	−	−	−	−	12.677	−0.364	3.750	−	−	−
Philippines	10.727	−1.338	−4.602	−	−	−	15.422 ^a	−0.168	−3.639	−	−	−
Singapore	15.433	−13.938	−14.710	−6.122	−1.118	−1.445	14.856	−2.455	−2.834	−13.304	2.203	17.782 ^a
Taiwan	12.831 ^a	−7.306 ^a	−3.066 ^a	−11.941	6.926 ^a	8.599 ^a	−	−	−	−11.839	5.367	4.362
Thailand	−	−	−	−	−	−	10.850 ^a	−1.618	−0.602	−	−	−

^a, ^b and ^c respectively denote statistical significance at a 1-, 5- and 10-percent level. Statistical significance is determined using the standard *t*-statistic. s_t^+ and s_t^- respectively denote the magnitude of positive and negative shocks at time *t*. The CARs are estimated using a dummy variable method similar to that of Karafiath (1988) but based on the GJR-GARCH estimation method. The full estimates are over a window of ten days but to conserve space we only show the measures across a limited window. The values of the CARs are in percentages.

Table 6

GJR-GARCH estimates for the volatility of the ARs following positive and negative shocks over the pre- and post-Asian crisis periods.

Panel A: Pre-crisis period							Panel B: Post-crisis period						
Country	Day 0	Day1	Day[1,2]	Day 0	Day1	Day[1,2]	Day 0	Day1	Day[1,2]	Day 0	Day1	Day[1,2]	
	Positive shocks of $+3\% < s_t^+ < +5\%$			Negative shocks of $-3\% > s_t^- > -5\%$			Positive shocks of $+3\% < s_t^+ < +5\%$			Negative shocks of $-3\% > s_t^- > -5\%$			
Hong Kong	1.376 ^a	0.275	0.055	2.084 ^a	-0.621 ^a	-0.616 ^a	0.159	-3.640 ^a	0.068	1.120 ^a	-0.141	0.001	
India	2.039 ^a	1.757 ^a	0.938 ^a	1.346 ^a	0.956 ^a	0.502 ^a	0.102	-0.805 ^b	-0.400 ^b	1.437 ^a	-1.023 ^b	-0.745 ^a	
Indonesia	3.158 ^a	0.765 ^b	0.505 ^a	-3.678 ^a	-0.400	-0.329 ^b	0.909 ^a	0.087	-0.005	1.537 ^a	-0.079	0.056	
Korea	0.251 ^a	-0.045	-0.0650 ^c	0.314 ^a	-0.105	-0.102 ^b	1.037 ^a	1.214 ^a	0.596 ^a	1.169 ^a	0.646 ^a	0.380 ^a	
Malaysia	0.401 ^b	-0.515 ^b	-0.145	1.633 ^a	-0.548	-0.280 ^c	-1.581 ^a	-0.153	-0.094	1.769 ^a	0.390	0.108	
Pakistan	0.967 ^a	-0.512	-0.433 ^b	1.031 ^a	-1.417 ^a	-0.515 ^a	-1.767 ^a	-1.173 ^a	-0.374 ^b	2.170 ^a	-0.005	0.046	
Philippines	1.512 ^a	0.296	0.072	2.110 ^a	1.299 ^a	0.666 ^a	-2.341 ^a	0.379 ^c	0.177	0.464 ^a	-1.031 ^a	-0.525 ^a	
Singapore	1.052 ^a	-0.238	-0.640 ^a	1.899 ^c	-1.888	-0.564	0.959 ^a	-0.278	-0.176	1.684 ^a	0.551	0.302	
Taiwan	0.928 ^a	0.144	0.135 ^c	0.894 ^a	-0.378 ^a	-0.203 ^a	-1.773 ^a	0.144	0.128	1.081 ^a	-0.302	-0.164	
Thailand	0.966 ^a	-0.735 ^b	-0.392 ^a	2.667 ^a	0.738 ^c	-0.187	1.142 ^a	0.305	0.156	-2.101 ^a	0.427	0.276	
	Positive shocks of $+5\% \leq s_t^+ < +10\%$			Negative shocks of $-5\% \geq s_t^- > -10\%$			Positive shocks of $+5\% \leq s_t^+ < +10\%$			Negative shocks of $-5\% \geq s_t^- > -10\%$			
Hong Kong	-2.636 ^a	-3.019 ^a	-1.275 ^a	6.133 ^a	-0.774	-0.443	-0.258	-0.880	-0.511	3.936 ^a	0.594	0.114	
India	2.219 ^a	-6.051 ^a	-3.293 ^a	2.666 ^a	0.096	-0.207	7.867 ^a	4.499 ^a	2.365 ^a	7.065 ^a	0.605	-0.560	
Indonesia	22.834 ^a	13.317 ^a	7.010 ^a	3.896 ^a	-1.987 ^c	-2.114 ^a	5.450 ^a	4.388 ^a	1.990 ^a	3.459 ^a	-2.362 ^a	-1.368 ^a	
Korea	0.086	-0.680 ^a	-0.364 ^a	1.245 ^a	-1.030 ^a	-0.749 ^a	1.773 ^a	1.971 ^a	1.061 ^a	2.841 ^a	0.173	0.112	
Malaysia	-1.679 ^a	-1.977 ^a	-0.930 ^a	4.420 ^a	-0.829	-0.776	7.064 ^a	5.460 ^a	2.890 ^a	1.180 ^a	-4.832 ^a	-2.062 ^a	
Pakistan	5.764	-2.163	-1.253	2.030	-3.183	-2.494 ^c	2.507 ^b	-3.022 ^a	-2.274 ^a	4.550 ^a	-1.801	-1.049	
Philippines	4.4161 ^a	2.701 ^a	1.316 ^b	3.146 ^a	-0.827	-0.336	3.191 ^a	1.775 ^c	0.503	8.148 ^a	5.271 ^a	2.715 ^a	
Singapore	7.294 ^c	2.604	1.257	5.994 ^c	-6.087 ^c	-2.512	1.117	-1.108	-0.835	2.578 ^a	-4.337 ^a	-2.767 ^a	
Taiwan	1.520 ^a	-0.958 ^b	-0.343 ^c	2.341 ^a	-1.147 ^a	-0.593 ^a	-2.988 ^a	-1.123 ^a	-0.448 ^b	2.238 ^a	-1.637 ^c	-1.018 ^a	
Thailand	2.742 ^b	-0.687	-0.441	4.491 ^a	-3.638 ^a	-1.716 ^a	3.420 ^a	-0.353	-0.215	2.199 ^a	-1.893 ^b	-1.280 ^a	
	Positive shocks of $s_t^+ \geq +10\%$			Negative shocks of $s_t^- \leq -10\%$			Positive shocks of $s_t^+ \geq +10\%$			Negative shocks of $s_t^- \leq -10\%$			
Hong Kong	13.235 ^a	-3.731	-0.995	82.577 ^a	60.047 ^a	19.160 ^a	-3.993	-12.361 ^a	-8.867 ^c	18.912 ^c	7.105	4.307	
India	8.054 ^a	3.455	2.129	1.918	-7.793 ^a	-3.953 ^b	-	-	-	2.106	-27.238 ^a	-12.829 ^a	
Indonesia	24.978	-95.817 ^a	-9.749 ^a	-0.595 ^a	-40.850 ^a	-3.932 ^a	-1.525	-10.077 ^a	-4.321 ^a	8.942 ^c	-12.191 ^a	-7.387 ^a	
Korea	-	-	-	1.108	-11.898 ^a	-5.849 ^a	-1.548	-3.415	-1.441	2.892	-12.149 ^a	-5.998 ^a	
Malaysia	-6.009	-9.625	-1.547	25.101 ^b	-6.788	-10.252 ^a	3.475	-7.888 ^b	-6.090 ^a	42.935 ^b	20.136	10.519	
Pakistan	-	-	-	-	-	-	-21.825 ^b	-37.023 ^a	-15.997 ^a	-	-	-	
Philippines	-5.842	-12.345 ^a	-6.769 ^c	-	-	-	-2.575	-11.972 ^a	-5.823 ^a	-	-	-	
Singapore	-104.818	-125.362	-50.503 ^c	63.279	-6.606	-12.610 ^a	-7.117 ^b	-31.029	-9.616 ^a	30.309	2.074	-14.241 ^b	
Taiwan	7.124 ^a	-10.445 ^a	-6.996 ^a	17.328 ^a	0.299	-0.262	-	-	-	-18.557 ^a	-31.601 ^a	-15.201 ^a	
Thailand	-	-	-	-	-	-	0.474	-7.754 ^a	-3.237 ^a	-	-	-	

^a, ^b and ^c respectively denote statistical significance at a 1-, 5- and 10-percent level. Statistical significance is determined using the standard *t*-statistic. s_t^+ and s_t^- respectively denote the magnitude of positive and negative shocks at time *t*. The volatility coefficients are estimated using a dummy variable method similar to that of Karafiath (1988). Day[1] denotes the change in volatility for day one whilst Day[1,2] denotes the change in volatility across days one and two. The volatility coefficients are multiplied by 10⁴. The full estimates are over a window of ten days but to conserve space we only show the measures across a limited window.

The results also suggest that much of the evidence in support of overreaction and return continuations might be associated with the change in risk and return around the financial crisis.

4.4.2. Volatility estimates

We also examine the volatility estimates for the pre- and post-crisis periods. These results are shown in Table 6. For the pre-crisis period, positive shocks within the range of $+3\% < s_t^+ < +5\%$ are followed by insignificant volatility coefficients for most indexes. Only four indexes carry significant volatility estimates and these are of different signs. Negative shocks of within $-3\% > s_t^- > -5\%$ are also followed by a mix of positive and negative day one coefficients. Positive shocks within $+5\% < s_t^+ < +10\%$ and negative shocks within $-5\% > s_t^- > -10\%$ are followed by negative day one coefficients in half of the cases. The remaining day one coefficients are largely insignificant. The number of significant day-one coefficients declines for larger trigger values. The results for the post-crisis period are largely similar to those of the pre-crisis period.

In general, the volatility coefficients are negative on average and they tend to decline over time whilst still remaining significant. This finding does not support the UIH. There is a greater tendency for the day one coefficients to be significant relative to the pre- and post-crisis period. Also, relative to the full period, the significant coefficients of the pre- and post-crisis periods become insignificant over time at a faster rate.

5. Conclusion

This empirical study examines the short-term reaction of ten Asian stock indexes following large price shocks. We use both OLS and GARCH-based estimation methods to generate the CARs over a window of ten days after the shocks. Our results based on the symmetric GARCH and GJR-GARCH methods are generally similar; so we focus mainly on the OLS and GJR-GARCH results. There is substantial variation in the effects of shocks across the ten indexes indicating that the price reaction varies by country. This feature can be due to differences in the way investors process unexpected information in those countries, but we leave this aspect for further research. There are also differences in the results due to the estimation method. Specifically, for the full period, the OLS method provides stronger support for return continuations, particularly following positive shocks within $+5\% < s_t^+ < +10\%$ and negative shocks within $-5\% \geq s_t^- > -10\%$. There is some support for market efficiency, but this support is not as strong compared with return continuations. There is also mixed support for market efficiency and overreaction following positive shocks of $s_t^+ \geq +10\%$. However, overreaction is more pronounced following negative shocks of $s_t^- \leq -10\%$.

The GJR-GARCH results contrast substantially with those of the OLS for the full period. Return continuations dominate following positive shocks within the range of $+3\% < s_t^+ < +5\%$ whilst market efficiency dominates following negative shocks within $-3\% > s_t^- > -5\%$. Larger positive and negative trigger values largely provide support market efficiency. This finding is strongest following shocks of $s_t^+ \geq +10\%$ and $s_t^- \leq -10\%$ and here, all support for return continuations and the overreaction hypothesis completely disappears.

The volatility estimates are typically negative and larger shocks give rise to larger volatility estimates. Our results do not support the UIH. Furthermore, the markets appear more efficiency over the post-Asian financial crisis. We still do not find support for the UIH over the pre- and post-Asian financial crisis.

Since we find that return continuations dominate at small trigger values whilst overreaction and/or EMH is more pronounced at larger trigger values, it appears that the results obtained depend on the magnitude of the shock. Specifically, prior studies that support overreaction or market efficiency tend to employ relatively large trigger values (see e.g., Brown and Harlow, 1988).¹⁵ In contrast, Lasfer et al. (2003) find support for return continuations using a trigger value within a small range of the standard deviation. If investor over-confidence and self-attribution can explain price overreaction and momentum around public events (see Daniel et al., 1998), our results demonstrate a related reaction in the very short-term for unexpected events. Furthermore, the choice of the estimation method leads to different results about price reaction. The greater support for market efficiency under the GARCH-based methods is in line with Fama's (1998) view that the evidence on short- to long-term market anomalies can be model dependent.¹⁶

¹⁵ Of course, individual stock prices exhibit more variability than stock indexes meaning that the largest trigger values for the ARs of stocks will be larger than the largest trigger values for the ARs of stock indexes.

¹⁶ Specifically, Fama (1998) argues that the evidence on long-term overreaction is as common as the evidence on underreaction, leading to support for market efficiency. He also suggests that the apparent short- to long-term anomalies are model dependent.

Appendix A

Selected prior empirical studies of price reaction following large price shocks.

Empirical study	Period of study	Stock market	Data frequency	Estimation method	Using percentage of shock	EMH	Return continuations	Over-reaction	UIH
Ajayi et al. (2006)	1990–2001	Five U.S. stock indexes	Daily	Symmetric GARCH/ asymmetric GARCH	✓				✓
Akhigbe et al. (1998)	1992	NYSE stocks	Daily	Standard linear	✓	✓		✓	
Atkins and Dyl (1990)	1975–1984	NYSE stocks	Daily	Standard linear	✓	✓		✓	
Bowman and Iversion (1998)	1976–1986	New Zealand stocks	Weekly	Standard linear	✓			✓	
Bremer et al. (1997)	1981–1991	Nikkei 300 stocks	Daily	Standard linear	✓			✓	
Bremer and Sweeney (1991)	1962–1986	U.S. Fortune 500 stocks	Daily	Standard linear	✓			✓	
Brown and Harlow (1988)	1946–1983	U.S. stocks	Monthly	Standard linear	✓		✓	✓	
Brown et al. (1988)	1962–1985	U.S. stocks	Daily	Standard linear	✓				✓
Cox and Peterson (1994)	1963–1991	NYSE, AMEX, NMS stocks	Daily	Standard linear	✓			✓	
Ferri and Chung-Ki (1996)	1962–1991	S&P 500 index	Daily	Standard linear	×			✓	
Howe (1986)	1963–1981	ASE and NYSE stocks	Weekly	Standard linear	✓			✓	
Lang and Mullineaux (1994)	1964–1989	NYSE, AMEX stocks	Daily	Standard linear	✓			✓	
Larson and Madura (2003)	1988–1995	NYSE stocks	Daily	Standard linear	✓			✓	
Lasfer et al. (2003)	1989–1998	39 national stock indexes	Daily	Standard linear	×		✓		
Lehmann (1990)	1962–1986	NYSE, AMEX stocks	Weekly	Standard linear	×			✓	
Park (1995)	1984–1987	All NASDAQ/NMS stocks	Daily	Standard linear	✓			✓	
Renshaw (1984)	1928–1981	ASE and NYSE stocks	Weekly	Standard linear	✓			✓	
Schnuseberg and Madura (2001)	Various starts to 1997	Six U.S. indexes	Daily	Standard linear	×		✓	✓	✓

Notes: EMH denotes the efficient market hypothesis. UIH denotes the uncertainty information hypothesis. For the percentage of shock column, × indicates that some other method of identifying the shock is used.

References

- Ajayi, A., Medhian, S., Perry, M.J., 2006. A test of US equity market reaction to surprises in an era of high trading volume. *Applied Financial Economics* 16, 461–469.
- Akhigbe, A., Gosnell, T., Harikumar, T., 1998. Winners and losers on NYSE: a re-examination using daily closing bid-ask spreads. *Journal of Financial Research* 21, 53–64.
- Atkins, A., Dyl, E., 1990. Price reversals, bid-ask spreads, and market efficiency. *Journal of Financial and Quantitative Analysis* 25, 535–547.
- Bekaert, G., Harvey, C., Lundblad, C., 2005. Does financial liberalization spur growth? *Journal of Financial Economics* 77, 3–55.
- Black, F., 1976. Studies of stock price volatility changes. *Proceedings of the 1976 Meeting of the American Statistical Association, Business and Economical Statistics section*, pp. 177–181.
- Bowman, R.G., Iversion, D., 1998. Short-run overreaction in New Zealand stock market. *Pacific-Basin Finance Journal* 6, 475–491.
- Bremer, M., Sweeney, R., 1991. The reversal of large stock-price decreases. *Journal of Finance* 46, 747–754.
- Bremer, M., Hiraki, T., Sweeney, R., 1997. Predictable patterns after large stock price changes on the Tokyo stock exchange. *Journal of Financial and Quantitative Analysis* 32, 345–365.
- Brown, K., Harlow, W., 1988. Market overreaction: magnitude and intensity. *Journal of Portfolio Management* 14, 6–13.

- Brown, S., Warner, J., 1980. Measuring security price performance. *Journal of Financial Economics* 8, 205–258.
- Brown, K., Harlow, W., Tinic, S., 1988. Risk aversion, uncertain information, and market efficiency. *Journal of Financial Economics* 22, 355–385.
- Christie, A., 1982. The stochastic behavior of common stock variances — value, leverage and interest rate effects. *Journal of Financial Economics* 10, 407–432.
- Corrado, C., 1989. A nonparametric test for abnormal security-price performance in event studies. *Journal of Financial Economics* 23, 385–395.
- Cox, D., Peterson, D., 1994. Stock returns following large one-day declines: evidence on short-term reversals and long-term performance. *Journal of Finance* 49, 255–267.
- Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. *Journal of Finance* 53, 1839–1885.
- De Bondt, W., Thaler, R., 1985. Does the stock market overreact? *Journal of Finance* 40, 793–805.
- Engle, R., Ng, V., 1993. Measuring and testing the impact of news on volatility. *Journal of Finance* 48, 1749–1778.
- Engle, R., Ito, T., Lin, W., 1990. Meteor showers or heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market. *Econometrica* 58, 525–542.
- Fama, E., 1998. Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics* 49, 283–306.
- Ferri, M.G., Chung-Ki, M., 1996. Evidence that the market overreacts and adjusts: an undeniable feature of daily stock price movements. *Journal of Portfolio management* 22, 71–76.
- French, K., Schwert, G., Stambaugh, R., 1987. Expected stock returns and volatility. *Journal of Financial Economics* 19, 3–29.
- Glosten, L., Jagannathan, R., Runkle, D., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance* 48, 1779–1801.
- Howe, J., 1986. Evidence on stock market overreaction. *Financial Analysts Journal* 42, 74–77.
- Jegadeesh, N., Titman, S., 1993. Returns to buying winning and selling losers: implications for stock market efficiency. *Journal of Finance* 48, 65–91.
- Kalay, A., Lowenstein, U., 1985. Predictable events and excess returns. *Journal of Financial Economics* 14, 423–449.
- Karafiath, I., 1988. Using dummy variables in the event methodology. *The Financial Review* 23, 351–357.
- Lang, Y., Mullineaux, D., 1994. Overreaction and reverse anticipation: two related puzzles? *Journal of Financial Research* 17, 31–43.
- Larson, S., Madura, J., 2003. What drives stock price behavior following extreme one-day returns? *Journal of Financial Research* 24, 113–127.
- Lasfer, M., Melink, A., Thomas, D., 2003. Short-term reaction of stock markets in stressful circumstances. *Journal of Banking and Finance* 27, 1959–1977.
- Lehmann, B., 1990. Fads, martingales, and market efficiency. *Quarterly Journal of Economics* 105, 1–28.
- Maroney, N., Naka, A., Wansi, T., 2004. Changing risk, returns and leverage; the 1997 Asian financial crisis. *Journal of Financial and Quantitative Analysis* 39, 143–166.
- Park, J., 1995. A market microstructure explanation for predictable variations in stock returns following large price changes. *Journal of Financial and Quantitative Analysis* 30, 241–256.
- Pesenti, P., Tille, C., 2000. The economics of currency crises and contagion: an introduction. *Federal Reserve Bank of New York, Economic Policy Review* 6, 3–16.
- Pindyck, R., 1984. Risk, inflation, and the stock market. *American Economic Review* 74, 334–351.
- Renshaw, E., 1984. Stock market panics: a test of the efficient market hypothesis. *Financial Analysts Journal* 40, 48–51.
- Savickas, R., 2003. Event-induced volatility and tests for abnormal performances. *Journal of Financial Research* 26, 165–178.
- Schnusenberg, O., Madura, J., 2001. Do US stock market indexes over- or underreact? *Journal of Financial Research* 24, 179–204.
- Zhang, X., 2006. Information uncertainty and stock returns. *Journal of Finance* 61, 105–137.