The Impact of Short Selling on the Price–Volume Relationship: Evidence from Hong Kong*

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Abstract

This paper considers the relationship between traded volume and volatility. We employ short sales data to discriminate between transactions that close existing long positions and transactions that establish new short positions. We test for, and where appropriate, incorporate non–linearity and asymmetry into the modelling process. The evidence supports a non-linear, bi-directional relationship between volume and volatility. The results suggest (i) that the market displays greater volatility following a period of short selling and (ii) that asymmetric responses to positive and negative innovations to returns appear to be exacerbated by short selling.

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There is a well-documented positive relationship between stock return volatility and contemporaneous trading volume (see Karpoff, 1987 p. 113 for a summary). More recent research on this issue however, suggests that this association may be more complicated than was previously thought. For example, Hiemstra and Jones (1994), Ratner and Leal (2001) and Chen, Firth and Rui (2001) find significant bi-directional causality between returns and volume. Evidence of a relationship between past returns and volume has been documented which has been attributed to tax effects (Lakonishok and Smidt, 1989) and the rate at which stocks incorporate information (Chordia and Swaminathan, 2000). Freund and Webb (1999) considered trading volume on the NASDAQ, NYSE and AMEX and conclude that the type and quantity of information driving trade is different on the NASDAQ compared to the other two exchanges.

The purpose of this paper is to furnish further evidence as to the nature of the relationship between share price volatility and traded volume. Much of the existing literature, Tauchen and Pitts (1983), Lamoureaux and Lastrapes (1990), Gallant et al, (1992), *inter alia*, assumes that the volume-price change relationship is monotonic and linear. Where non-linearity is parameterised, the literature has tended to impose symmetry and/or constant correlation on the conditional variance-covariance structure. Such linearity and/or symmetry assumptions may be tenuous and conceivably lead to model mis-specification and ultimately result in unreliable inference. The model specification adopted in our paper is unique in that we will test for and, where appropriate, incorporate potential sources of non-linearity and asymmetry into the modelling process.

Once source of the asymmetry discussed in the literature is motivated by the observation that that negative shocks elicit a greater response in volatility than positive shocks of an equal magnitude, see Black (1976), Christie (1982), Nelson (1990), Campbell and Hentschel (1992) Engle and Ng (1993), Glosten, Jagannathan and Runkle (1993) and Bekaert and Wu (2000) *inter alia*. In this paper, it is argued that a second form of asymmetry exists which the previous literature has failed to take into account. This asymmetry arises from the activities of traders in the market engaged in short selling. An informed trader will take a short position in the equity of a firm on the basis of unfavourable prospects regarding the company's future (Diamond and Verrecchia, 1987). This is distinct from the sales undertaken by traders whose motives are exogenously determined by such factors as portfolio rebalancing, the need for liquidity and so on. The trading activity of short sellers may, therefore, provide important information as to the amount and type of news available for a given company. Specifically, short sales signify bad news (see Senchack and Starks, 1993, Choie and Hwang, 1994, Asquith and Meulbroek, 1996 and Aitken, Frino, McCorry and Swan, 1998), which the literature has found causes markets to overreact compared to good news (see Kaminsky and Schmukler, 1999 and Veronesi, 1999). In addition to return volatility asymmetry we hypothesise that the volume volatility relationship displays asymmetry. Market responses to a given level of traded volume will differ depending on whether or not short sellers are active in the market on that day.[1]

To test this hypothesis we employ data drawn from the Hong Kong market. As brokers are legally obliged to identify short sales to the exchange as the orders are executed, the Hong Kong market provides an ideal data set. We can distinguish between the sales that close out long positions from those transactions used to open short positions. The remainder of this paper proceeds as follows. The next section defines some important concepts and details the hypotheses to be tested. Section III provides some institutional information about the Hong Kong stock market and the history of short selling on this exchange. Section IV formally describes the data and, based on the identified properties, outlines an appropriately specified model. The estimation results are presented and discussed in section V. Finally, section VI provides a brief summary and some concluding comments.

II. Traded Volume-Price Volatility Relationship Hypothesis Tests

A common theme in the literature is that “it takes volume to make prices move”. Campbell, Grossman and Wang (1993), Blume, Easley and O’Hara (1994), He and Wang (1995), Chordia and Swaminathan (2000) and Suominen (2001), *inter alia*, all predict causal relations from volume to volatility. It is possible however, that a feedback loop may exist in which case price movements might cause further volume, see Hiemstra and Jones (1994), and Chen, Firth and Rui (2001), *inter alia*. As such, the first hypothesis to be tested in this paper is that of no-Granger Causality from volume to prices. A second hypothesis to be tested is of no reverse causality from prices to volume.

Let $r_{i,t}$ represent the return to stock *i* on day *t* and $V_{i,t}$ denote a measure of the corresponding volume. Suominen (2001) introduced a model in which private information about equity returns is available in any given period with some probability that changes stochastically over time. Traders estimate the availability of private information using lagged volume and, as such, modify their trading strategies as the probability of private information entering the market increases. The trades of informed traders (volume) therefore, reveals private information which impacts on prices (volatility) and hence, a positive relationship is derived.

Proposition 4 in Suominen (2001) states that the covariance between current and past return variances is positive which motivates our third hypothesis that the returns display ARCH effects.

Proposition 5 of Suominen (2001) maintains that the conditional variance of return displays mean reverting behaviour, that is $E_t\left(h_{i,r,t+1}\right) < h_{i,r,t}$ when $h_{i,r,t+1} > \sigma^2_{i,r}$, and $E_t\left(h_{i,r,t+1}\right) > h_{i,r,t}$ when $h_{i,r,t+1} < \sigma^2_{i,r}$. Here $h_{i,r,t} = \text{var}\left[r_{i,t} \mid \Omega_t\right]$, and $E_t(.)$ denotes the expectation operator conditioned on the public information set Ω_t. The fourth hypothesis therefore, is of mean reversion in returns variance.

In addition to these four hypotheses suggested by the literature, this paper tests several new hypotheses relating to the existence of asymmetries in the relationship between traded volume and price volatility. The leverage effect suggests that a negative return innovation leads to higher responses in volatility than a positive innovation of equal size. Following Kroner and Ng (1998) and Bekaert and Wu (2000) we may define asymmetric volatility as:

$$\text{var}\left[r_{i,t+1} \mid \Omega_t, \varepsilon_{i,r,t} < 0\right] - \sigma^2_{i,r,t} > \text{var}\left[r_{i,t+1} \mid \Omega_t, \varepsilon_{i,r,t} > 0\right] - \sigma^2_{i,r,t} \qquad (13)$$

In other words, negative unanticipated returns result in the expectation of conditional volatility of return being revised upwards. On the other hand, the downward revision of volatility in response to a positive unanticipated return innovation is relatively smaller. Ng and Kroner (1998) refer to such effects as "own variance asymmetry". The fifth hypothesis to be tested in this paper specifies a null of no own variance asymmetry in returns. In a similar fashion, a sixth hypothesis may be specified which tests the null of no own variance asymmetry in volume, defined as:

$$\text{var}\left[V_{i,t+1} \mid \Omega_t, \varepsilon_{i,V,t} < 0\right] - \sigma^2_{i,V,t} > \text{var}\left[V_{i,t+1} \mid \Omega_t, \varepsilon_{i,V,t} > 0\right] - \sigma^2_{i,V,t} \qquad (14)$$

A seventh hypothesis test is for the null of the presence of cross variance asymmetry between volume and volatility where returns are said to display cross variance asymmetry if:

$$\operatorname{var}\left[r_{i,t+1} \mid \Omega_t, \varepsilon_{i,V,t} < 0\right] - \sigma_{r,t}^2 > \operatorname{var}\left[r_{i,t+1} \mid \Omega_t, \varepsilon_{i,V,t} > 0\right] - \sigma_{i,r,t}^2 \tag{15}$$

while for volume to display cross variance asymmetry it must be the case that:

$$\operatorname{var}\left[V_{i,t+1} \mid \Omega_t, \varepsilon_{i,r,t} < 0\right] - \sigma_{i,V,t}^2 > \operatorname{var}\left[V_{i,t+1} \mid \Omega_t, \varepsilon_{i,r,t} > 0\right] - \sigma_{i,V,t}^2 \tag{16}$$

The final potential source of asymmetry tested in this paper relates to the trading presence of short sellers. A series, y_{it}, where $y_{i,t} = r_{i,t}, V_{i,t}$, is said to display short sales asymmetry if:

$$\operatorname{var}\left[y_{i,t+1} \mid \Omega_t, SS_{i,t} > 0\right] - \sigma_{i,y,t}^2 > \operatorname{var}\left[y_{i,t+1} \mid \Omega_t, SS_{i,t} = 0\right] - \sigma_{i,y,t}^2 \tag{17}$$

In this case short selling results in the expectation of the conditional volatility of y_i being revised upwards. Thus, our eighth hypothesis is that the conditional variances of returns and volume display short sales asymmetry.

III. Short Selling and the Hong Kong Stock Market

Hong Kong has a long history of securities trading with records dating back to 1866 and the formation of the Association of Stockbrokers in Hong Kong in 1891, later renamed the Hong Kong Stock Exchange (HKSE) in 1914. Although the HKSE has faced competition from a number of competing exchanges over the years, it is currently the sole stock exchange in the region (see Brockman and Cheung, 1998 for a more detailed historical overview). More recently, the HKSE merged with the Hong Kong Futures Exchange and the Hong Kong Securities Clearing Company to form Hong Kong Exchanges and Clearing Limited (HKEx). This new organisation, which merges the three major financial market organisations operating in Hong Kong, was listed on the HKSE in June 2000.

The trading environment of the HKSE represents one of the simplest forms of market making procedures of any exchange in the global financial arena. The exchange has no opening call market, no price controls, no liquidity providers or specialists and no special arrangements for closing. The exchange is an order driven market with continuous trading during opening hours whereby designated members place limit orders into the Automatic Order Matching and Execution System (AMS) which are prioritised by price and executed in order of time of arrival to the exchange.

The HKSE first introduced short selling in January 1994, under a pilot program, which designated 17 eligible stocks. Under the new rules, investors were able to sell short provided they have an exercisable and unconditional right to vest the stock and the trade was not to be made at a price below the best current ask price (the 'tick rule').[2] The tick rule is enforced by the exchange through its AMS system, with members of the exchange being obliged to establish whether or not the client meets these vesting rules prior to placing the order (HKSE Eleventh Schedule, Point 7). Penalties exist for both members and the investors who fail to comply with these rules, although there is some evidence that the deterrents are insufficient. Breaches of the short selling regulations in Hong Kong are common and the exchange investigates hundreds of transactions each year although only a few result in prosecution.[3]

In March 1996, the tick rule was abandoned in favour of 'naked' short selling and the list of eligible stocks was expanded. In August 1998, the Hong Kong government spent US$12.5b buying stocks and futures to support a market that was perceived to be labouring under heavy speculative selling pressure arising from the 1997 Asian crisis. To curb future short selling and prevent a repeat of previous events, a host of new rules were introduced in September, 1998 including the reinstatement of the tick rule, albeit in a modified form in which an exemption was made for short sales transactions undertaken by stock options market makers in the course of performing their duty.

The broker identifies short selling transactions to the exchange at the time of placing the order in the AMS. This information is then made available to the market via the limit order book, which flags all short sales. In addition, exchange members are also required to keep a ledger with specific details of each individual short selling transactions and this must be made available to the exchange at any time. As such, detailed short sales records are kept for trades made on the HKSE and the exchange makes this information available in the form of a daily report. This report summarises total daily short sales volume and short sales value for each individual stock and is usually made available after a 24-hour delay.

IV. Data Description and Model Specification

IIIA. Data Description

The stocks chosen for analysis in this paper consist of the 14 companies that were included in the pilot short selling program and are still trading. In addition, the current constituents of the Hang Seng Index were sampled providing a total sample of 21 companies[4]. Daily price, total transactions volume and short sales volume data for each of the companies were sampled over the period 30 January 1994 to 5 September 2001. The start date of the sample coincides with the introduction of short selling to the HKSE. To conserve space this paper reports results only for Cathay Pacific (Cathay), Cheung Kong, Hong Kong and China Gas (HK&C Gas), HSBC Holdings (HSBC), Henderson Investment (Henderson), and Hutchison Telecom (Hutchison).

The results for the unreported companies are qualitatively consistent with those presented and are available on request from the authors.

The returns series were calculated as $r_{i,t} = 100 \times \ln\left(P_{i,t} / P_{i,t-1}\right)$, where prices are measured in HK$. The volume series is measured in number of shares traded per day and changes in traded volume were calculated as $v_{i,t} = \ln\left(V_{i,t} / V_{i,t-1}\right)$, where i indexes the company.

Table I about here

Table I presents some summary statistics for the returns, $r_{i,t}$ (panel A), raw volume, $V_{i,t}$ (panel B), and raw short sales volume, $S_{i,t}$ (panel C), data for each of the companies. The average return for 4 of the 6 companies was positive; the lowest mean return is –0.03% for Cathay, while the highest mean return is 0.05% for HSBC. In general, Hong Kong stock prices exhibit a great deal of variation with one-day returns of in excess of 20% common across the sample. Henderson experienced the largest one-day fall of 19% on 28th October 1997 when the price fell from $6.20 to $5.10. The standard deviation for these returns data is greater than that generated by the market index. Not surprisingly, given these large price movements, the Jarque-Bera test for normality was rejected in each instance. HSBC was the most heavily traded stock in our sample and also exhibited the greatest level of short interest, registering short sales 85.85% of the time with an average daily short sold volume of 397,862 shares. Henderson exhibited the lowest volume of short sales, on average 95,550 shares were sold short each day, and short selling only occurring 36.14% of the time.

Following Engle and Ng (1993), Gallant, Rossi and Tauchen (1993), Henry (1998) and Kroner and Ng (1998), *inter alia*, the data were filtered to remove any seasonal or deterministic components from the conditional mean of the series. The approach taken in this paper is to estimate a 12th order VAR in returns and changes in volume, i.e.:

$$Y_{i,t} = \sum_{l=1}^{12} \Gamma_l Y_{t-l} + \Phi D_t + \Psi SS_{i,t-1} + \Xi U_t + \Lambda G_t + \varepsilon_{i,t} \tag{1}$$

where $\Gamma_l, \Phi, \Psi, \Xi,$ and Λ represent parameter matrices, D_t, represents a set of daily dummies, $SS_{i,t}$ represents a dummy variable identifying whether or not there was short selling in the equity of firm i on day t, G_t is a dummy variable capturing the effects of the heavy short selling on the 28th of August, 1998 when the Hong Kong government stood against the market, and U_t is a dummy variable which captures the March, 1996 to August, 1998 period of naked short selling. The residual vector from (1):

$$\varepsilon_{i,t} = \begin{bmatrix} \tilde{r}_{i,t} \\ \tilde{v}_{i,t} \end{bmatrix} \tag{2}$$

contains the filtered returns, $\tilde{r}_{i,t}$, and volume changes, $\tilde{v}_{i,t}$ which have a zero mean and are free from serial correlation by construction. There remains the possibility of heteroscedasticity however, and to this end we perform a series of tests designed to detect evidence of conditional heteroscedasticity and asymmetry in $\tilde{r}_{i,t}$, and $\tilde{v}_{i,t}$. The Engle (1982) LM test for ARCH of order p tests the null of zero slopes in the regression:

$$y_{i,t}^2 = \phi_0 + \sum_{m=1}^{p} \phi_m y_{i,t-m}^2 + u_{i,t} \tag{3}$$

The test is performed as $T \cdot R^2$ from estimation of (3) for $y_{i,t} = \tilde{r}_{i,t}, \tilde{v}_{i,t}$, where T represents the sample size. A similar test for dependence in the conditional second moment of the data may be performed using a Ljung-Box test on the squared residuals. The first two rows of panel A and B in Table II present the results of LM and Ljung-Box tests for up to fifth order ARCH applied to the returns and volume data. In all cases the null of no ARCH was rejected at all usual levels of confidence for the returns data. For the changes in volume data the null of no ARCH was rejected for all series except Cathay, where the results were marginal and for HK&C Gas where the data failed to reject the null of no-fifth order ARCH. In both these cases however, there was strong evidence of first order ARCH.

Table II about here

A common finding in the literature on stock market volatility is that negative shocks cause more volatility than positive shocks of equal magnitude. Such asymmetry in volatility, often referred to as the 'leverage effect', has been documented using univariate ARCH models by Nelson (1991) Engle and Ng (1993), Glosten, Jagannathan and Runkle (GJR, 1993), *inter alia*. Brooks, Henry and Persand (2002) use a multivariate asymmetric GARCH approach to model and price this asymmetry. Panel A and B of Table II report the Engle and Ng (1993) tests for size and sign bias applied to returns and volume. Define $N_{i,t}$ as in indicator dummy that takes the value 1 if $y_{i,t} < 0$ and zero otherwise. The test for sign bias is based on the significance of ϕ_1 in:

$$y_{i,t}^2 = \phi_0 + \phi_1 N_{i,t-1} + u_{i,t} \tag{4}$$

Where $u_{i,t}$ is a white noise error term and $y_{i,t} = \tilde{r}_{i,t}, \tilde{v}_{i,t}$. If positive and negative innovations have differing impacts on the conditional variance of $y_{i,t}$, then ϕ_1 will be statistically significant in (4).

It may also be the case that the source of the bias is caused not only by the sign, but also the magnitude of the shock. The negative size bias test is based on the significance of the slope coefficient ϕ_2 in:

$$y_{i,t}^2 = \phi_0 + \phi_2 N_{i,t-1} y_{i,t-1} + u_{i,t} \qquad (5)$$

Likewise, defining $P_{i,t} = 1 - N_{i,t}$, a similar test may be performed for positive size bias.

Finally, the Engle and Ng (1993) joint test for asymmetry in variance is based on the regression:

$$y_{i,t}^2 = \phi_0 + \phi_1 N_{i,t-1} + \phi_2 N_{i,t-1} y_{i,t-1} + \phi_3 P_{i,t-1} y_{i,t-1} + u_{i,t} \qquad (6)$$

Significance of the parameter ϕ_1 indicates the presence of *sign bias*. That is, positive and negative realisations of ε_t affect future volatility differently to the prediction of the model. Similarly significance of ϕ_2 or ϕ_3 would suggest *size bias*, where not only the sign, but also the magnitude of innovation in growth is important. A joint test for sign and size bias, based upon the Lagrange Multiplier Principle, may be performed as $T \cdot R^2$ from the estimation of (6). The results in Table II suggest significant evidence of negative size bias in the returns data that is consistent with the presence of a leverage effect. There is less evidence of asymmetry however, in the change in volume data.

Panel A and B of Table II also present the results from a test for bias in the conditional variance arising from the failure to adequately capture the effects of short selling. Again this test may be performed using a Lagrange Multiplier approach based on the auxiliary regression:

$$y_{i,t}^2 = \phi_0 + \phi_4 SS_{i,t-1} + u_t \qquad (7)$$

where $SS_t = 1$ if short selling occurred on day *t* and zero otherwise. The results of this procedure provide strong evidence of short sales asymmetry in the returns and volume data, implying that volatility tends to be higher following a period of short selling.

IIIB. Model Specification

The data description suggests that the filtered returns display significant evidence of (i) ARCH, (ii) negative size bias and (iii) bias to short sales activity. The filtered volume data, display strong evidence of ARCH and bias to short sales activity and weaker evidence of size bias. Consequently, we fit the following model to the filtered returns ($\tilde{r}_t$) and volume ($\tilde{v}_t$) data:

$$\begin{aligned} Y_{it} &= \varepsilon_{i,t} \\ Y_{i,t} &= \begin{bmatrix} \tilde{r}_{i,t} \\ \tilde{v}_{i,t} \end{bmatrix}; \varepsilon_{i,t} = \begin{bmatrix} \varepsilon_{i,\tilde{r},t} \\ \varepsilon_{i,\tilde{v},t} \end{bmatrix} \end{aligned} \tag{8}$$

Assuming $\varepsilon_{i,t} \mid \Omega_t \sim (0, H_{i,t})$, where $H_{i,t} = \begin{bmatrix} H_{i,\tilde{r},t} & H_{i,\tilde{r}\tilde{v},t} \\ H_{i,\tilde{r}\tilde{v},t} & H_{i,\tilde{v},t} \end{bmatrix}$ and ε_t represents the innovation vector in (8), the bivariate GARCH(1,1) model may be written according to the parameterisation proposed by Engle and Kroner (1995), ie.:

$$H_{i,t} = C_0^{*'} C_0^* + A_{11}^{*'} H_{i,t-1} A_{11}^* + B_{11}^{*'} \varepsilon_{i,t-1} \varepsilon_{i,t-1}^{'} B_{11}^* \tag{9}$$

where:

$$C_0^* = \begin{bmatrix} c_{11}^* & c_{12}^* \\ 0 & c_{22}^* \end{bmatrix}; \; A_{11}^* = \begin{bmatrix} a_{11}^* & a_{12}^* \\ a_{21}^* & a_{22}^* \end{bmatrix}; \; B_{11}^* = \begin{bmatrix} b_{11}^* & b_{12}^* \\ b_{21}^* & b_{22}^* \end{bmatrix} \tag{10}$$

This BEKK parameterisation requires estimation of only 11 parameters in the conditional variance-covariance structure and guarantees $H_{i,t}$ positive definite. It is important to note that the BEKK model implies that only the magnitude and not the sign of innovations is important in determining current time-varying variances and covariances. This assumption of symmetric conditional variance-covariance matrices must be considered tenuous given the results presented in Table II and the existing body of evidence documenting the asymmetric response of equity volatility to positive and negative innovations of equal magnitude (see Engle and Ng, 1993, Glosten, Jagannathan and Runkle, 1993, Kroner and Ng, 1996, and Brooks, Henry and Persand, 2002, *inter alia*).

Defining $\xi_{i,\tilde{r},t} = \min\left\{\varepsilon_{i,\tilde{r},t}, 0\right\}$ and $\xi_{i,\tilde{v},t} = \min\left\{\varepsilon_{i,\tilde{v},t}, 0\right\}$, the BEKK model in (9) may be extended to allow for asymmetric responses as:

$$H_{i,t} = C_0^{*'} C_0^* + A_{11}^{*'} H_{i,t-1} A_{11}^* + B_{11}^{*'} \varepsilon_{i,t-1} \varepsilon_{i,t-1}^{'} B_{11}^* + D_{11}^{*'} \xi_{i,t-1} \xi_{i,t-1}^{'} D_{11}^* \tag{11}$$

where $\xi_{i,t} = \begin{bmatrix} \xi_{i,\tilde{r},t} \\ \xi_{i,\tilde{v},t} \end{bmatrix}$ and $D_{11}^* = \begin{bmatrix} d_{11}^* & d_{12}^* \\ d_{21}^* & d_{22}^* \end{bmatrix}$.

The symmetric *BEKK* model in (9) is given as a special case of (11) where all the elements of D_{11}^* equal zero.

Kroner and Ng (1998) analyse the asymmetric properties of time-varying covariance matrix models, identifying three possible forms of asymmetric behaviour. First, the covariance matrix displays *own variance* asymmetry if the conditional variance of $\tilde{r}_t\left(\tilde{v}_t\right)$, is affected by the sign of the innovation in $\tilde{r}_t\left(\tilde{v}_t\right)$. Second, the covariance matrix displays *cross variance asymmetry* if the conditional variance of $\tilde{r}_t\left(\tilde{v}_t\right)$ is affected by the sign of the innovation in $\tilde{v}_t\left(\tilde{r}_t\right)$. Finally, if the covariance of returns $H_{\tilde{r}\tilde{v},t}$ is sensitive to the sign of the innovation in return or volume, the model is said to display *covariance asymmetry*.

To allow for the asymmetric response to short sales behaviour recall the dummy variable SS_t, which takes the values 1 if there was short selling on day *t*, and zero otherwise. We may define $\varpi_{i,t} = \begin{bmatrix} \varpi_{i,\tilde{r},t} \\ \varpi_{i,\tilde{s},t} \end{bmatrix} = \begin{bmatrix} SS_{i,t}\tilde{r}_t \\ SS_{i,t}\tilde{v}_t \end{bmatrix}$ and further extend (11) as:

$$H_{i,t} = C_0^{*'} C_0^* + A_{11}^{*'} H_{i,t-1} A_{11}^* + B_{11}^{*'} \varepsilon_{i,t-1} \varepsilon_{i,t-1}^{'} B_{11}^* + D_{11}^{*'} \xi_{i,t-1} \xi_{i,t-1}^{'} D_{11}^* + E_{11}^{*'} \varpi_{i,t-1} \varpi_{i,t-1}^{'} E_{11}^* \tag{12}$$

Where $E_{11}^* = \begin{bmatrix} e_{11}^* & e_{12}^* \\ e_{21}^* & e_{22}^* \end{bmatrix}$

The model specified in (12) conforms to the properties of the data described in Table II and will be used to model the returns, volume and short sales data for each of the Hong Kong companies in our sample.

V. Empirical Results

VA. Model estimates and diagnostics

Quasi-maximum likelihood estimation of the model given in equation (12) provided the individual parameter estimates which are reported in Table III along with the associated robust standard errors (see Bollerslev and Wooldrige, 1992). The estimates of the main-diagonal elements of A_{11}^{*} are significant in all cases indicating that past return (volume) volatility impacts on current volatility in returns (volume) as is typical of GARCH processes. The off-diagonal elements of A_{11}^{*} are generally significant except for Henderson, and suggest that volatility transmissions exist between volume and returns for these two companies. The significance of all of the estimated main-diagonal elements in the B_{11}^{*} matrix indicates that past innovations to returns and volume are significant determinants of current volatility. Further, the significance of the off-diagonal elements in the B_{11}^{*} matrix for Cathay and HSBC suggest that innovations in returns impact on the volatility of volume and vice versa. Overall, these results are suggestive of a non-linear feedback loop in which volume acts as a proxy for the news that drives volatility. These volatility innovations in turn, reveal information to the market motivating further trades and so increasing volume.

Table III about here

The significance of all of the d_{11}^{*} parameters in the D_{11}^{*} matrix highlights strong evidence of own variance asymmetry in the returns data. The d_{22}^{*} parameter is only significant for HSBC and HK&C Gas which is indicative of an absence of own variance asymmetry in volume. This evidence, coupled with the results of the size and sign bias tests suggest that total volume does not display strong evidence of own variance asymmetry. Cross variance asymmetry and covariance asymmetry appear present for all of the data except Cathay as one or both of the d_{12}^* and d_{21}^* parameters are significant for the other companies.

The impact of the presence of short sellers in the market is captured in the E_{11}^* matrix. With the exception of HK&C Gas, all of the e_{11}^* coefficients are significant which suggests that the own variance asymmetry in the returns data is enhanced during episodes of short selling which is consistent with our main hypothesis. Further, the significance of the e_{21}^* coefficient in the estimated equations for HK&C Gas, Henderson, Hutchison and Cheung Kong suggests the cross variance and covariance asymmetry is also heightened when short sellers are active in the market. The almost uniform insignificance of e_{22}^* is further evidence against own variance asymmetry in volume.

Overall, the models appear well specified and Table IV presents some model diagnostic test results. The standardised residuals for company *i*, defined as $z_{i,j,t} = \varepsilon_{i,j,t} / \sqrt{h_{i,j,t}}$ for $j = \tilde{r}, \tilde{v}$, and their corresponding squares, satisfy the null of no fourth order linear dependence of the Ljung-Box (1978) *Q(12)* and *Q²(12)* tests. Similarly there is no evidence of twelfth order serial dependence in $z_{i,j,t}$ and $z_{i,j,t}^2$ at the 5% level.[5]

Table IV about here

The model predicts that $E\left(\varepsilon_{i,t}^2\right) = h_{i,t}$ for $i = \tilde{r}, \tilde{v}$ and $E\left(\varepsilon_{i,\tilde{r},t}\varepsilon_{i,\tilde{v},t}\right) = h_{i,\tilde{r}\tilde{v},t}$. The moment conditions for the conditional variances may be tested using

$$h_{i,t} = \phi_0 + \phi_1 \varepsilon_{i,t}^2 + v_{i,t} \tag{18}$$

where v_t is a white noise error. Similarly the moment condition for the conditional covariance may be tested using

$$h_{i,\tilde{r}\tilde{v},t} = \phi_0 + \phi_1 \varepsilon_{i,\tilde{r},t} \varepsilon_{i,\tilde{v},t} + v_{i,t} \tag{19}$$

Pagan and Sabau (1992) argue that the null hypothesis $\phi_1 = 1$ may be tested using the usual LM approach. We refer to these moment condition tests as P-S_R and P-S_V, for the conditional variances of return and volume and PS_{RV}, for the conditional covariance. These conditions are generally not rejected by the data at the 5% level.[6]

VB. News Impact Surfaces

Taken together, the estimates of (12) suggest that news about returns and volume spill over to impact on the volatility of $\tilde{r}_{i,t}$ and $\tilde{v}_{i,t}$. Bad news in the form of a negative return innovation or a fall in volume however, will lead to higher levels of volatility than a positive shock of equal magnitude. Further, where short sellers are present in the market, these asymmetries are heightened.

A useful approach to gain an appreciation of the documented asymmetries is through the use of news impact surfaces. Following Ng and Kroner (1998), and Brooks Henry and Persand (2002), news impact surfaces for company *i* may be constructed in the region $\varepsilon_{i,j,t} = [-5, 5]$ for $j = \tilde{r}, \tilde{v}$ holding information at time *t*-1 and before constant. Figures 1-12 display the variance and covariance news impact surfaces for each of the stocks implied by the coefficient estimates of the model displayed in Table 3. The odd numbered figures are constructed assuming that there was no short selling on day *t-1*. The even numbered figures allow for the impact of short sales. Comparison of the odd and even figures allows us to gauge the impact of short sales on the returns- trading volume relationship.

Some caution should be exercised in interpreting the news impact surfaces for large absolute values of $\varepsilon_{i,j,t}$ as there are relatively few extreme outliers in the data. Despite this caveat, the asymmetry in variance and covariance is clear. The sign and magnitude of return and volume shocks have clearly differing impacts on elements of $H_{i,t}$. The major difference between the two sets of figures is the increase in the asymmetry following a day where short selling occurs. The effect of short selling seems to be an increase in the response of volatility to news. The effect appears particularly strong for the conditional variance of volume for HK&C Gas, Henderson, Hutchison and Cheung Kong and is driven by the relatively large e_{21}^{*} parameter estimate reported for these stocks.

VC. Hypothesis tests

A number of hypotheses about the relationship between price movements and volume, and the effect of short selling on this relationship can be tested using the estimated BEKK model for each of the stocks in our sample. The model can also be used to test a number of hypotheses related to the presence of asymmetries and non-linearities in the data. The first hypothesis tested is that of no-causality from volume to returns and the results are presented in the first row of Table V. In all cases but HK&C Gas the data fail to reject the null of no-causality. Similarly, row 2 of Table V reveals that the data fail to reject the null of no reverse causality from prices to volume for all series except HK&C Gas and Cheung Kong. Thus, the data provides only minimal evidence of linear causality between returns and volume and vice versa.

Table V about here

The third hypothesis to be tested is that current and past returns volatilities are positively correlated and, consistent with our expectations, there is overwhelming evidence in support of this hypothesis. First, both LM and Ljung-Box tests for ARCH in returns reported in Table II are uniformly significant at all usual levels of confidence. Second, the estimates of a_{11}^{*} and b_{11}^{*} reported in table 3 are significant across each returns series. Finally, the third row of Table V presents the first order autocorrelation estimate for return volatility and the estimated coefficient is significantly different from zero in each case supporting the null hypothesis.

The model of Suominen (2001) suggests that the conditional variance of return displays mean reversion, ie. $E_t\left(h_{i,\tilde{r},t+1}\right) < h_{i,\tilde{r},t}$ when $h_{i,\tilde{r},t+1} > \sigma_{i,\tilde{r}}^2$, and $E_t\left(h_{i,\tilde{r},t+1}\right) > h_{i,\tilde{r},t}$ .when $h_{i,\tilde{r},t+1} < \sigma_{i,\tilde{r}}^2$. This provides a fourth hypothesis that may be tested as $H_0 : \rho = 1$ against the alternative hypothesis, $H_A : \rho < 1$. The test is implemented using the auxiliary regression:

$$h_{i,\tilde{r},t} = \mu + \rho h_{i,\tilde{r},t-1} + u_{i,t} \tag{20}$$

The fourth row of Table V presents the relevant t-statistic from the estimated regression equation and using the standard Dickey-Fuller critical values there is no evidence to support the null of infinite persistence in $h_{i,\tilde{r},t}$ which is consistent with the theoretical predictions of the Suominen model.

Our fifth hypothesis concerns the existence of 'leverage effects' or asymmetry in volatility in the returns data and there is overwhelming evidence in support of the hypothesis. First, the negative sign bias tests reported in Table II for $\tilde{r}_{i,t}$ are uniformly significant. Second, many of the individual estimates of the elements of the D_{11}^{*} matrix in (12) are significant as shown in table 3. In particular the significance of d_{11}^{*} for all series considered is consistent with own-variance asymmetry in returns. A very different story emerges however, when we consider the sixth hypothesis of the presence of asymmetric variance in volume. The parameter estimates presented in Table II show only limited evidence of such behaviour as only Cathay and HK&C Gas reject the null of the joint test for size and sign bias. The insignificance of the d_{22}^{*} parameter in Table 3, for all but HSBC and HK&C Gas, is further evidence as to the absence of significant own-variance volatility in volume. Finally, there is evidence in favour of the seventh hypothesis of the presence of cross-variance asymmetry as the many of the off-diagonal elements in D_{11}^{*} are significant. Except for Cathay Pacific, at least one, and often both of d_{12}^{*} and d_{21}^{*} are significant.

It is possible to perform a joint test of the null $H_0 : d_{m,n} = 0, \forall m, n$ on the estimates of (12) and the results are presented in the fifth row of Table V. These Wald test results confirm the presence of GJR type asymmetry.[7] On balance, the asymmetry would appear to be a function of asymmetric responses to unanticipated returns. In terms of returns volatility, we find strong evidence of own-variance asymmetry. The conditional volatility of volume and the conditional covariance between volume and returns are also found to respond asymmetrically to return innovations.

Central to this study is the hypothesised presence of short sales asymmetry. The test results in the final two rows of Table II provide strong evidence of such effects. Further evidence of short sales asymmetry may be garnered from a Wald test of the null hypothesis $H_0 : e_{m,n} = 0, \forall m, n$ in (12). The test results are reported in row 6 of Table V and the null is clearly rejected in every instance. In general, the significance of the e_{11}^{*} and e_{21}^{*} parameters is consistent with the main response to short selling volume being through the conditional variance of returns, see also figures 1-12. Short sales result in a higher than expected level of return volatility, which in turn may spill-over to generate higher than expected volume volatility.

As a final test of the nature of the asymmetries in our data, we tested for the null of symmetric volatility $H_0 : e_{m,n} = d_{m,n} = 0, \forall m,n$ and the null of diagonality of the conditional variance structure $H_0 : a_{m,n} = b_{m,n} = d_{m,n} = e_{m,n} = 0,\ \forall m \neq n$. The Wald statistics and p-values are presented in the final two rows of Table V. In both cases the data failed to support the null at all usual levels of significance.

VI. Conclusions

Using daily data on Hong Kong equity prices and volumes this paper re-considers the volume-return relationship. Unlike the previous literature discussing this issue, this paper tests for, and where appropriate, incorporates potential sources of non – linearity and asymmetry into the modelling process.

The literature provides strong evidence of time-variation and asymmetry in the variance-covariance structure of asset returns. One potential explanation for such asymmetry in variance is the so-called 'leverage effect' of Black (1976) and Christie (1982). In brief, this theory proposes that as equity values fall, the weight attached to debt in a firm's capital structure rises, *ceteris paribus*. This induces equity holders, who bear the residual risk of the firm, to perceive the stream of future income accruing to their portfolios as being relatively more risky. An alternative view of the dynamics by which this asymmetry may work is provided by the 'volatility-feedback' hypothesis of Campbell and Hentschel (1992). Assuming constant dividends, if expected returns increase when stock return volatility increases, then stock prices should fall following a rise in volatility. Bekaert and Wu (2000) reject the pure leverage effect in favour of volatility-feedback as an explanation for asymmetric volatility in a sample of Nikkei 225 stocks. Consistent with these results, the evidence presented in this paper implies that the Hong Kong market will be relatively more volatile when prices are trending downwards.

This paper documents a new form of asymmetry in the dynamic process that determines stock return volatility. The source of this asymmetry is the trading activity of short sellers. Short sales are motivated by bad news about a company's future prospects. The trading activity of short sellers (volume) reveals their informational advantage to noise traders and, as markets typically overreact to bad news compared to good news, elicits a larger response in volatility compared to a day in which short sellers are absent from the market. This is not to suggest however, that volume drives prices as much of the theoretical literature suggests and many empirical studies implicitly assume. Rather, the parameter estimates of our model clearly indicate the presence of a strong non-linear bi-directional relationship between innovations to volume and returns volatility.

These results suggest that the standard model of trading volume driving the first two conditional moments of returns may be mis-specified. The evidence supports non-linear bi-directional relationship between trading volume and price volatility. A number of important asymmetries exist in this relationship. The data display greater volatility in response to a price fall than to a price rise of equal magnitude. Furthermore, the evidence suggests that the market displays greater volatility following a period of short selling than would otherwise have been the case. Finally, the asymmetric response of returns volatility to positive and negative innovations to returns appears to be exacerbated by short selling.

References

Aitken M.J., A. Frino, M.S. McCorry and P.L. Swan, (1998) “Short sales are almost instantaneously bad news: Evidence from the Australian stock exchange”, *The Journal of Finance*, **53**, 2205-2223.

Asquith, P. and L. Meulbroek, (1996) “An empirical investigation of short interest”, *Working Paper 96-012*, Harvard University.

Assogbavi, T., N. Khoury, and P. Yourougou, (1995) “Short interest and the asymmetry of the price-volume relationship in the Canadian stock market”, *Journal of Banking and Finance*, **19**, 1341 – 1358.

Bekaert, G. and G. Wu (2000) “Asymmetric volatility and risk in equity markets”, *The Review of Financial Studies*, **13**, 1- 42.

Black, F. (1976) “Studies in price volatility changes”, Proceedings of the 1976 Meeting of the Business and Economics Statistics Section, *American Statistical Association*, 177-181.

Bollerslev, T. and J.M. Wooldridge, (1992) “Quasi-maximum likelihood estimation and inference in models with time varying covariances”, *Econometric Reviews,* **11**, 143-72.

Braun, P.A., D.B. Nelson and A.M. Sunier (1995) “Good news, bad news, volatility, and betas”, *Journal of Finance*, **50**, 1575-1603.

Brockman P. and D.Y. Cheung (1998) “Inter- and intra-day liquidity patterns on the stock exchange of Hong Kong”, *Journal of International Financial Markets, Institutions and Money*, **8**, 277-98.

Brooks, C., Ó.T. Henry and G. Persand, (2002) “The effect of asymmetries on optimal hedge ratios”, *Journal of Business*,**72,** in press.

Campbell, J. and L. Hentschel, (1992) “No news is good news: An asymmetric model of changing volatility in stock returns”, *Journal of Financial Economics*, **31**, 281-318.

Chamberlain, T.W., C.S. Cheung and C.C.Y. Kwan, (1991) “Volume-price change relations and the costly short sales hypothesis: Some empirical tests” *Canadian Journal of Administrative* Sciences, **8**, 175 - 8.

Chen, G.M., M. Firth and O.M. Rui (2001) “Dynamic relation between stock returns, trading volume, and volatility”, *Financial Review*, **36**, 153-73.

Cho, Y.H. and R.F. Engle (1999) “Modeling the impacts of market activity on bid-ask spreads in the option market” Working Paper: 99/05, University of California, San Diego, Department of Economics.

Christie, A. (1982) “The stochastic behaviour of common stock variance: Value, leverage and interest rate effects”, *Journal of Financial Economics*, **10**, 407-432.

Choie, K.S. and S.J. Hwang, (1994) “Profitability of short-selling and exploitability of short information”, *Journal of Portfolio Management*, **20**, 33-38.

Chordia,T. and B. Swaminathan,(2000) “Trading volume and cross-autocorrelations in stock returns”, *Journal of Finance*, **55**, 913-35.

Copeland, T.E. (1976) “A model of asset trading under the assumption of sequential information arrival”, *Journal of Finance*, **31**, 1149 – 68.

Diamond, D.W. and R.E. Verrecchia, (1987) “Constraints on short-selling and asset price adjustment to private information”, *Journal of Financial Economics*, **18**, 277-311.

Engle, R.F. (1982) “Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation”, *Econometrica*, **50**, 987-1007.

Engle, R.F and K. Kroner, (1995) “Multivariate simultaneous generalized ARCH”, *Econometric Theory*, **11**, 122-150.

Engle, R.F. and V. Ng, (1993) “Measuring and testing the impact of news on volatility”, *Journal of Finance*, **48**, 1749-1778.

Epps, T.W. (1975) “Security price changes and transaction volumes: Theory and evidence”, *American Economic Review*, **65**, 586 – 597.

Freund, S.W. and G.P. Webb (1999) “Recent growth in NASDAQ trading volume and its relation to market volatility”, *Journal of Financial Research,* **22**, 489-501.

Gallant, A.R., P.E. Rossi and G. Tauchen (1993) “Stock prices and volume”, *Review of Financial Studies*, **5**, 199-242.

Glosten, L.R., R. Jagannathan and D. Runkle, (1993) “On the relation between the expected value and the volatility of the nominal excess return on stocks”, *Journal of Finance*, **48**, 1779-1801.

Hiemstra, C. and J.D. Jones (1994) “Testing for linear and non-linear Granger causality in the stock price-volume relationship”, *Journal of Finance*, **49**, 1639-1664.

Henry, Ó.T. (1998) “Modelling the asymmetry of stock market volatility”, *Applied Financial Economics*, **8**, 145 - 153.

Jennings, R.H., L.T. Starks and J.C. Fellingham (1981) “An equilibrium model of asset trading with sequential information arrival”, *Journal of Finance*, **26**, 143 – 161.

Jones, C.M., G. Kaul and M.L. Lipson, (1994) “Transactions, volume and volatility” *Review of Financial Studies*, **7**, 631 – 51.

Kaminsky, G.L. and S.L. Schmukler, (1999) "What triggers market jitters? A chronicle of the Asian crisis", *Journal of International Money and Finance,* **18**, 537-60.

Karpoff, J.M. (1987), "The relation between price changes and trading volume: A survey", *Journal of Financial and Quantitative Analysis*, **22**, 109-126.

Karpoff, J.M. (1988) "Costly short sales and the correlation of returns with volume", *Journal of Financial Research*, **51**, 173 – 188.

Kocagil, A.E. and Y. Shachmurove (1998) "Return-volume dynamics in futures markets", *Journal of Futures Markets*, **18**, 399 – 426.

Kroner, K.F., and V.K. Ng, (1998) "Modeling asymmetric comovements of asset returns", Review of Financial Studies, **11**, 817-44.

Lakonishok, J. and S. Smidt, (1989) "Past price changes and trading volume", *The Journal of Portfolio Management*, **15**, *18-24*.

Lamoureaux, C.G. and W.D. Lastrapes (1990) "Heteroskedasticity in stock return data: Volume versus GARCH effects", *Journal of Finance*, **45**, 221-29.

Ljung, G. and G. Box (1978) "On a measure of lack of fit in time series models", *Biometrika*, **66**, 67-72.

Nelson, D. (1991) "Conditional heteroscedasticity in asset returns: A new approach", *Econometrica*, **59**, 347-370.

Pagan, A.R. and H. Sabau (1992) "Consistency tests for heteroscedasticity and risk models, *Estudios Economico*, **7**, 3-30.

Ranter, M. and R.P.C. Leal (2001) "Stock returns and trading volume" Evidence from the emerging markets of Latin America and Asia", *Journal of Emerging Markets*, **6**, 5 – 22.

Senchack, A.J. and L.T. Starks, (1993) "Short-sale restrictions and market reaction to short-interest announcements", *Journal of Financial and Quantitative Analysis*, **28**, 177-94.

So, A. (1998) "Naked short selling inaction under fire" *Hong Kong Standard*, Article 159, Dow Jones Publications Library.

Suominen, M. (2001) "Trading volume and information revelation in stock markets", *Journal of Financial and Quantitative Analysis*, **36**, 545-565

Tauchen, G. and M. Pitts (1983) "The price variability-volume relationship on speculative markets", *Econometrica*, **51**, 485-505.

Veronesi, P. (1999) "Stock market overreaction to bad news in good times: A rational expectations equilibrium model", Review of Financial Studies, **12**, 975-1007.

Footnotes

1. An asymmetry in the volume response to different price changes has been found in the literature (see Epps, 1975, Jennings et al., 1981, Karpoff, 1987, 1988, Chamberlain et al., 1991, Assogbavi, 1995, and Kocagil and Shachmurove, 1998) which has been attributed to heterogenous expectations (Epps, 1975, Copeland 1976) and the costs of short selling (Karpoff, 1988). The asymmetry introduced in this paper is different to the extent that it is short sales which proxies news and so drives volatility. This causality is consistent with the theoretical models of the volume-volatility relationship (see Suominen, 2001 and Blume et al, 1994, *inter alia*) which show volume contains information about fundamental values.
2. The short selling rules on the HKSE are less restrictive than to those in the US (see Asquith and Meulbroek, 1996 for a summary).
3. In 1997, the HKSE conducted 764 investigations and prosecuted in 15 instances (So, 1998).
4. The sample excludes MTR, which is a newly listed company and does not provide enough data for analysis.
5. On the basis of $Q^2(12)$ though, there is some evidence of twelfth order dependence in the squared standardised residuals of the returns equation for Henderson.
6. The exceptions are for HK&C Gas which violates P-S_V and P-S_{RV} and Hutchison which violates PS_V.
7. A battery of Kroner and Ng (1998) type tests was performed on both the raw data and the standardised residuals. The results were consistent with the

conclusions above, namely the strongest evidence was for own variance asymmetry in the returns series. The standardised residuals were free from systematic bias indicated that the models were free from size, sign and quadrant bias. The results of these tests are available on request from the first author.

Table I: Summary Statistics

This table reports summary statistics for returns, total volume and short sales over the period 30 January 1994 to 5 September 2001. The returns series were calculated as $r_{i,t} = 100 \times \ln\left(P_{i,t} / P_{i,t-1}\right)$, where prices are measured in HK$. The volume series and short sales series are measured in number of shares traded per day

Company	Mean	Maximum	Minimum	Std. Dev.	Jarque-Bera P-value
			Panel A : Returns		
Hang Seng Index	0.0001	0.1726	-0.1472	0.0194	0.000
Cathay	-0.0003	0.1681	-0.1390	0.0266	0.000
HSBC	0.0005	0.1930	-0.1795	0.0197	0.000
HK&C Gas	0.0001	0.1405	-0.1091	0.0202	0.000
Henderson	-0.0002	0.2428	-0.1953	0.0284	0.000
Hutchison	0.0003	0.2163	-0.1255	0.0257	0.000
Cheung Kong	0.0002	0.2155	-0.1434	0.0256	0.000
			Panel B : Volume		
Cathay	3,843,867	92,630,000	225,000	4,409,696	0.000
HSBC	11,584,755	428,669,700	1,383,800	12,954,869	0.000
HK&C Gas	8,603,066	279,784,100	899,400	8,636,592	0.000
Henderson	3,093,643	65,081,600	151,000	2,995,453	0.000
Hutchison	6,660,772	233,239,300	1,046,700	6,583,725	0.000
Cheung Kong	5,923,648	176,133,900	620,800	6,290,416	0.000

Panel C : Short Sales[A]

	Mean	Maximum	Cumulative	% of Days in Sample with Short Selling
Cathay	211,212	7,784,000	270,563,000	53.79%
HSBC	397,862	15,373,600	509,660,700	85.87%
HK&C Gas	183,952	9,999,000	235,642,100	53.79%
Henderson	95,550	4,794,000	122,399,000	36.14%
Hutchison	338,805	24,305,000	434,009,000	82.44%
Cheung Kong	226,164	10,899,000	289,715,600	85.25%

Note: As short selling commenced for Henderson in June 1996, the sample period for the short sale summary statistics was estimated over a restricted sample period. The exclusion of these two years does not significantly alter these statistics as only a relatively small amount of short trading took place in this initial period.

Table II: Time Series Properties of the adjusted data

Day-of-week effects, vesting rule changes and Government intervention effects have been removed. The sample period is 30 January 1994 to 5 September 2001. ARCH(5) is the Engle (1981) LM test for up to fifth order ARCH. $Q^2(5)$ is a Ljung-Box test on the squared data. Negative sign, Negative size, Positive size and Joint test are Engle-Ng (1993) LM tests for asymmetry in variance. Short sales is an LM test for variance asymmetry as described in equation (7). Marginal significance levels displayed as [.]

	Cathay	HSBC	HK&C Gas	Henderson	Hutchison	Cheung Kong
Panel A: Returns, $\tilde{r}_{i,t}$						
ARCH(5)~$\chi^2(5)$	135.0153	433.8604	189.7874	137.6622	249.8244	191.8937
	[0.0000]	[0.0000]	[0.0000]	[0.00000]	[0.0000]	[0.0000]
$Q^2(5)$~$\chi^2(5)$	205.9978	614.4406	316.6134	216.3693	451.6341	33.7018
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Negative sign	-0.0319	1.4098	0.3596	-0.8599	1.4948	-0.1812
	[0.9745]	[0.1587]	[0.6924]	[0.3899]	[0.1351]	[0.8562]
Negative size	-4.0921	-13.1217	-7.9410	-5.5448	-10.0337	-8.3474
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Positive size	3.8492	0.26892	3.4515	2.3437	4.1060	4.0957
	[0.0001]	[0.0072]	[0.0006]	[0.0192]	[0.0000]	[0.0000]
Joint test ~$\chi^2(3)$	47.5330	224.8804]	104.5144	58.7284	161.2606	132.323
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Short Sales	4.8750	3.4625	1.9207	0.5723	3.2866	1.9028
	[0.0000]	[0.0005]	[0.0549]	[0.5672]	[0.0010]	[0.0572]
Panel B: Volume, $\tilde{v}_{i,t}$						
ARCH(5)~$\chi^2(5)$	10.2761	37.0312	5.9201	24.3106	24.0097	31.2526
	[0.0678]	[0.0000]	[0.3141]	[0.0002]	[0.0002]	[0.0000]
$Q^2(5)$~$\chi^2(5)$	11.0525	35.1528	6.1678	29.2418	24.4322	32.0515
	[0.0503]	[0.0000]	[0.2902]	[0.0000]	[0.0002]	[0.0000]
Negative sign	-0.1528	0.1743	0.9575	0.5639	-1.0774	0.4846
	[0.8786]	[0.8616]	[0.3384]	[0.5728]	[0.2815]	[0.6279]
Negative size	-1.4713	-0.7593	-1.0794	-1.0128	-0.9014	0.4113
	[0.1414]	[0.4478]	[0.2805]	[0.3112]	[0.3675]	[0.6809]
Positive size	0.6534	2.6533	0.6588	2.5830	2.3805	4.0796
	[0.5136]	[0.080]	[0.4929]	[0.0099]	[0.0174]	[0.0000]
Joint test ~$\chi^2(3)$	5.0993	12.5593	4.3010	16.9323	11.2041	23.7379
	[0.1647]	[0.0057]	[0.2307]	[0.0007]	[0.0107]	[0.0000]
Short Sales	-2.1125	-0.3088	-3.0264	-0.7976	-2.8291	-2.1164
	[0.0348]	[0.7575]	[0.0025]	[0.4252]	[0.0047]	[0.0344]

Table III: Multivariate GARCH Parameter Estimates

This table reports the parameter estimates for (12)

$$H_{i,t} = C_0^{*'}C_0^* + A_{11}^{*'}H_{i,t-1}A_{11}^* + B_{11}^{*'}\varepsilon_{i,t-1}\varepsilon_{i,t-1}^{'}B_{11}^* + D_{11}^{*'}\xi_{i,t-1}\xi_{i,t-1}^{'}D_{11}^* + E_{11}^{*'}\varpi_{i,t-1}\varpi_{i,t-1}^{'}E_{11}^*$$

where:

$$C_0^* = \begin{bmatrix} c_{11}^* & c_{12}^* \\ 0 & c_{22}^* \end{bmatrix}; A_{11}^* = \begin{bmatrix} a_{11}^* & a_{12}^* \\ a_{21}^* & a_{22}^* \end{bmatrix}; B_{11}^* = \begin{bmatrix} b_{11}^* & b_{12}^* \\ b_{21}^* & b_{22}^* \end{bmatrix}; D_{11}^* = \begin{bmatrix} d_{11}^* & d_{12}^* \\ d_{21}^* & d_{22}^* \end{bmatrix}; E_{11}^* = \begin{bmatrix} e_{11}^* & e_{12}^* \\ e_{21}^* & e_{22}^* \end{bmatrix}$$

with $\xi_{i,t} = \begin{bmatrix} \xi_{i,\tilde{r},t} \\ \xi_{i,\tilde{s},t} \end{bmatrix} = \begin{bmatrix} \min\{\tilde{r}_{i,t}, 0\} \\ \min\{\tilde{v}_{i,t}, 0\} \end{bmatrix}$ and $\varpi_{i,t} = \begin{bmatrix} \varpi_{i,\tilde{r},t} \\ \varpi_{i,\tilde{s},t} \end{bmatrix} = \begin{bmatrix} SS_{i,t}\tilde{r}_t \\ SS_{i,t}\tilde{v}_t \end{bmatrix}$;

Estimates are obtained using the BFGS numerical optimisation algorithm and the method of quasi-maximum likelihood. The sample period is from 30 January 1994 to 5 September 2001. Bollerslev-Wooldridge robust standard errors are displayed as (.). A single asterisk denotes significance at the 5% level.

	Cathay	HSBC	HK&C Gas	Henderson	Hutchison	Cheung Kong
c_{11}^*	0.1702	0.3191 *	0.3001 *	0.2526 *	0.2064	0.2941 *
	(1.6622)	(0.0174)	(0.0454)	(0.0950)	(0.1684)	(0.0912)
c_{12}^*	1.7174 *	-0.0423 *	0.0008	0.0145	-0.0825	0.0513
	(0.0859)	(0.0088)	(0.0246)	(0.0114)	(0.0626)	(0.1030)
c_{22}^*	1.7535 *	0.1947 *	0.2936 *	0.0672 *	0.3472 *	0.3508 *
	(0.0795)	(0.0027)	(0.0190)	(0.0142)	(0.0342)	(0.0084)
a_{11}^*	0.9741 *	0.9224 *	0.9109 *	0.9580 *	0.9313 *	0.9314 *
	(0.0093)	(0.0012)	(0.0100)	(0.0068)	(0.0139)	(0.0092)
a_{12}^*	-0.0089 *	0.0053 *	0.0128 *	-0.0009	0.0122 *	0.0113 *
	(0.0016)	(0.0007)	(0.0028)	(0.0006)	(0.0049)	(0.0040)
a_{21}^*	-0.1445 *	0.0784 *	0.0304	0.0153	0.4199 *	0.0057
	(0.0488)	(0.0287)	(0.0318)	(0.0120)	(0.1744)	(0.5505)
a_{22}^*	0.9042 *	0.8392 *	0.7495 *	0.9780 *	0.2821 *	0.3268 *
	(0.0421)	(0.0034)	(0.0342)	(0.0055)	(0.1533)	(0.0693)
b_{11}^*	0.1522 *	0.1971 *	0.2365 *	0.2062 *	0.1730 *	0.1882 *
	(0.0268)	(0.0267)	(0.0375)	(0.0204)	(0.0353)	(0.0318)
b_{12}^*	0.0184 *	0.0089 *	-0.0018	-0.0003	0.0042	0.0083
	(0.0054)	(0.0048)	(0.0059)	(0.0027)	(0.0051)	(0.0057)
b_{21}^*	0.2504 *	0.0245	0.0511	-0.0227	0.0522	0.1685
	(0.1040)	(0.0634)	(0.0779)	(0.0584)	(0.1733)	(0.2285)
b_{22}^*	0.2022 *	0.2276 *	0.1674 *	0.1742 *	0.2605 *	0.2735 *
	(0.0312)	(0.0234)	(0.0484)	(0.0162)	(0.0823)	(0.0517)

Table III Continued

d_{11}^{*}	0.1642 *	0.3576 *	0.4232 *	0.1961 *	-0.3840 *	-0.4111 *
	(0.0362)	(0.0373)	(0.0559)	(0.0438)	(0.0426)	(0.0302)
d_{12}^{*}	-0.0049	-0.0217 *	-0.0397 *	0.0046	0.0612 *	0.0612 *
	(0.0113)	(0.0108)	(0.0110)	(0.0041)	(0.0079)	(0.0134)
d_{21}^{*}	0.2737	0.1904	0.4810 *	-0.3123 *	0.1321	-0.3444
	(0.7932)	(0.1111)	(0.2028)	(0.1220)	(0.2370)	(0.3930)
d_{22}^{*}	0.0536	0.1249 *	0.1232 *	0.0046	0.0051	0.1269
	(0.1263)	(0.0427)	(0.0696)	(0.0416)	(0.0622)	(0.0998)
e_{11}^{*}	0.1440 *	0.1971 *	0.0418	-0.0842 *	0.0839 *	-0.3433 *
	(0.0326)	(0.0227)	(0.1245)	(0.0386)	(0.0280)	(0.0662)
e_{12}^{*}	0.0004	0.0069	-0.0016	-0.0022	0.0053	0.0068
	(0.0064)	(0.0059)	(0.0045)	(0.0034)	(0.0030)	(0.0043)
e_{21}^{*}	0.2279	-0.1789	-0.8803 *	0.7432 *	0.7336 *	0.8470 *
	(0.1451)	(0.2186)	(0.1608)	(0.1846)	(0.2690)	(0.1613)
e_{22}^{*}	-0.0075	0.1107 *	0.0425	0.0363	0.0666	-0.1163
	(0.0538)	(0.0524)	(0.0619)	(0.0436)	(0.1771)	(0.1299)

Table IV: Multivariate GARCH Diagnostic Tests

Tests were performed using the standardised residuals for company *i*, $z_{i,j,t} = \varepsilon_{i,j,t} / \sqrt{h_{i,j,t}}$ for $j = \tilde{r}, \tilde{v}$, and the corresponding squares obtained from the estimation of (12). The sample period is 30 January 1994 to 5 September 2001. Q(12) ($Q^2(12)$) is a Ljung-Box test for up to twelfth order serial correlation in $z_{i,j,t}$ and $z_{i,j,t}^2$ is distributed as $\chi^2(12)$. The model predicts that $E\left(\varepsilon_{i,t}^2\right) = h_{i,t}$ for $i = \tilde{r}, \tilde{v}$ and $E\left(\varepsilon_{i,\tilde{r},t}\varepsilon_{i,\tilde{v},t}\right) = h_{i,\tilde{r}\tilde{v},t}$. These moment conditions for the conditional variances may be tested using $h_{i,t} = \phi_0 + \phi_1\varepsilon_t^2 + q_t$ where q_t is a white noise error. The moment condition for the conditional covariance may be tested using $h_{i,\tilde{r}\tilde{v},t} = \phi_0 + \phi_1\varepsilon_{i,\tilde{r},t}\varepsilon_{i,\tilde{v},t} + q_t$. These are LM type tests and are distributed as $\chi^2(1)$ We refer to these moment condition tests as P-S_R and P-S_V, for the conditional variances of return and volume and PS_{RV}, for the conditional covariance. Marginal significance levels are displayed as [.].

	Cathay	HSBC	HK&C Gas	Henderson	Hutchison	Cheung Kong
$Q(12)_R \sim \chi^2(12)$	6.8919	19.8811	13.7508	14.2704	13.3291	8.8371
	[0.8647]	[0.0694	[0.3169]	[0.2838]	[0.4196]	[0.7168]
$Q^2(12)_R \sim \chi^2(12)$	4.9665	11.8504	4.2519	38.8061	7.8428	6.0844
	[0.9591]	[0.4578]	[0.9784]	[0.0001]	[0.7973]	[0.9118]
$Q(12)_V \sim \chi^2(12)$	17.6602	8.7096	13.6133	8.4536	10.1079	12.2447
	[0.1264]	[0.7275]	[0.3261]	[0.7488]	[0.6065]	[0.4262]
$Q^2(12)_V \sim \chi^2(12)$	3.7667	12.7860	3.3656	9.4785	8.6468	1.1116
	[0.9873]	[0.3848]	[0.9924]	[0.6616]	[0.7328]	[0.9997]
$P-S_R \sim \chi^2(1)$	0.8012	0.2097	0.4360	0.2821	0.0237	0.0056
	[0.3707]	[0.6469]	[0.5090]	[0.5953]	[0.8878]	[0.9401]
$P-S_V \sim \chi^2(1)$	1.7675	2.7882	5.8581	0.2874	9.5084	3.1933
	[0.1837]	[0.0950]	[0.0155]	[0.5918]	[0.0021]	[0.0739]
$P-S_{RV} \sim \chi^2(1)$	0.6234	1.1570	6.1168	0.0397	1.6512	0.0817
	[0.4298]	[0.2821]	[0.0134]	[0.8421]	[0.1988]	[0.7751]

Table V: Hypothesis Tests

Wald Statistics are calculated using the Bollerslev-Wooldridge approach. Asymptotic t-ratios are displayed as (.), while marginal significance levels are displayed as [.].

H1 - No causality from volume to returns, ie. $\tilde{v}_{i,t} \nrightarrow \tilde{r}_{i,t}$ where $\nrightarrow$ denotes "does not Granger cause".

H2 - No causality from returns to volume, ie. $\tilde{r}_{i,t} \nrightarrow \tilde{v}_{i,t}$. where $\nrightarrow$ denotes "does not Granger cause".

H3 - Current and past returns volatilities are uncorrelated, ie. $E\left[\sigma^2_{i,t+s}, \sigma^2_{i,t}\right] = 0$.

H4 - The variance of returns are mean reverting, ie. $\hat{\rho}=1$.

H5: - No GJR type asymmetry

H6: - No Short sales asymmetry

H7: - Diagonality of the variance covariance structure.

	Cathay	HSBC	HK&C Gas	Henderson	Hutchison	Cheung Kong
H1: $\tilde{v}_{i,t} \nrightarrow \tilde{r}_{i,t}$	0.8031 [0.6477]	0.8588 [0.5399]	1.9333 [0.0267]	0.7916 [0.6597]	0.9477 [0.4977]	1.1940 [0.2812]
H2: $\tilde{r}_{i,t} \nrightarrow \tilde{v}_{i,t}$.	0.7991 [0.6519]	1.7318 [0.0546]	2.0971 [0.0145]	1.1699 [0.2992]	1.3015 [0.2105]	2.2873 [0.0069]
H3: $E\left[\sigma^2_{i,t+s}, \sigma^2_{i,t}\right] = 0$	0.9899 (0.0033)	0.9519 (0.0071)	0.9349 (0.0082)	0.9437 (0.0076)	0.9539 (0.0069)	0.9642 (0.0061)
H4 (T- Ratio)	-3.0606	-6.7746	-7.9390	-7.4079	-6.6812	-5.8689
H5 $d_{m,m} = 0, \forall m,n \sim\chi^2(4)$	45.1403 [0.0000]	93.8164 [0.0000]	69.5811 [0.0000]	28.8990 [0.0000]	193.8994 [0.0000]	236.0527 [0.0000]
H6 $e_{m,n} = 0, \forall m,n \sim\chi^2(4)$	23.1470 [0.0000]	95.5926 [0.0000]	41.6134 [0.0000]	25.7094 [0.0000]	80.6334 [0.0000]	28.2411 [0.0000]
H7 $e_{m,n} = d_{m,n} = 0, \forall m,n \sim\chi^2(8)$	52.8406 [0.0000]	155.4738 [0.0000]	445.8640 [0.0000]	69.0065 [0.0000]	1310.9354 [0.0000]	590.7557 [0.0000]
$a_{m,n} = b_{m,n} = d_{m,n} = e_{m,n} = 0, \forall m \neq n \sim\chi^2(8)$	29.8089 [0.0000]	260.1783 [0.0000]	104.8759 [0.0000]	44.2128 [0.0000]	344.8527 [0.0000]	121.9431 [0.0000]

Figure 1 News Impact Surfaces : Cathay Pacific - No Short Sales

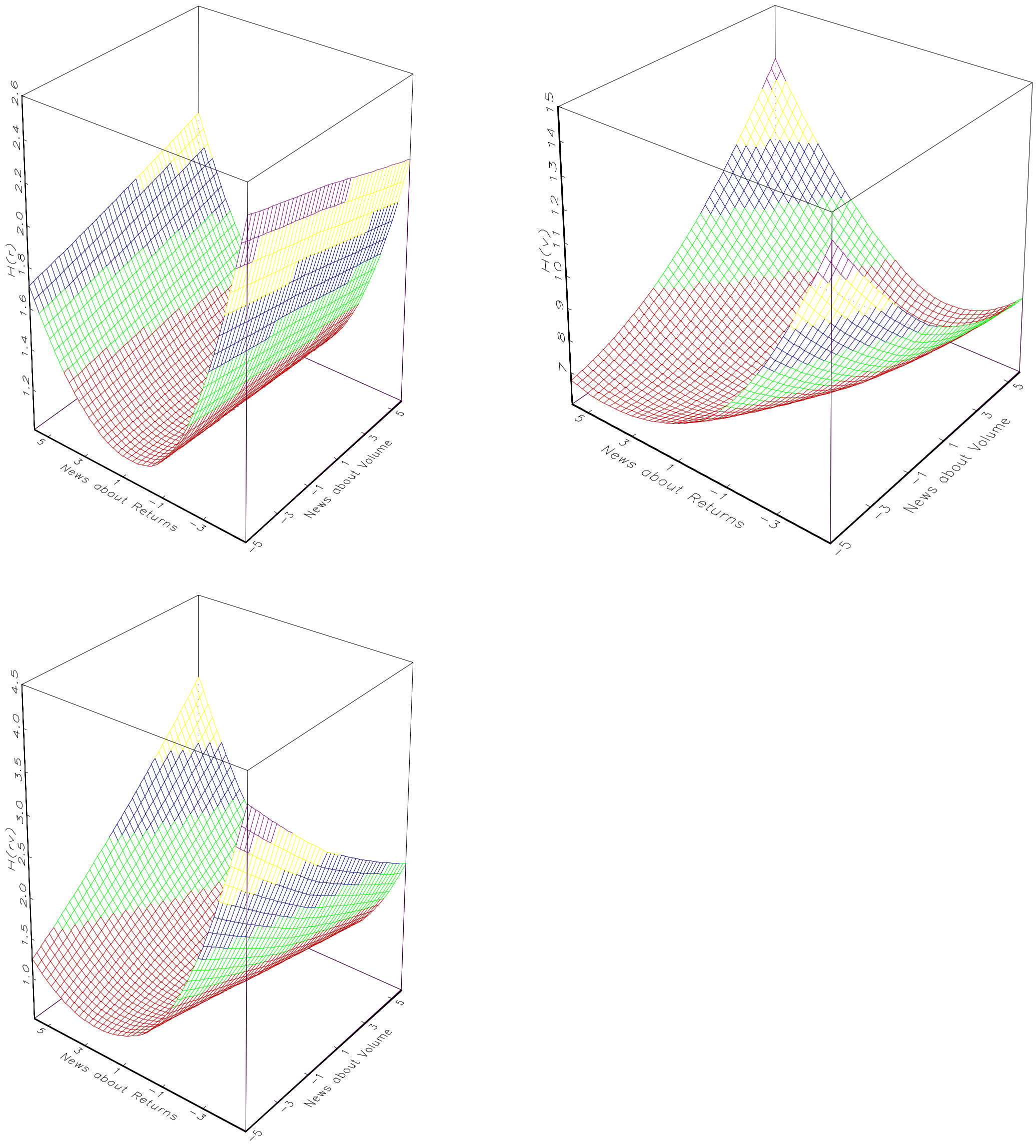


Figure 2: News Impact Surfaces : Cathay Pacific - Short Sales

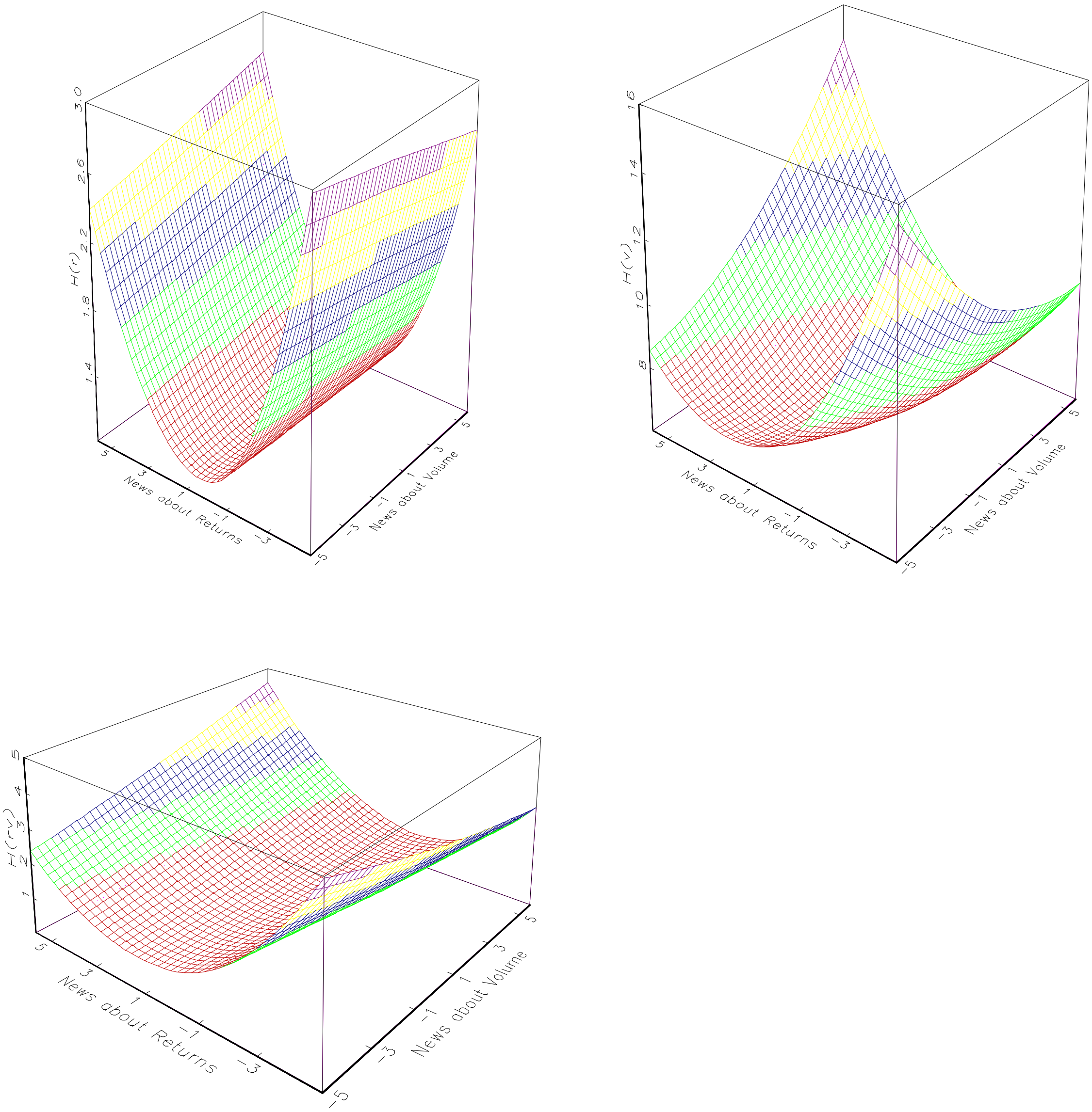


Figure 3: News Impact Surfaces : HSBC - No Short Sales

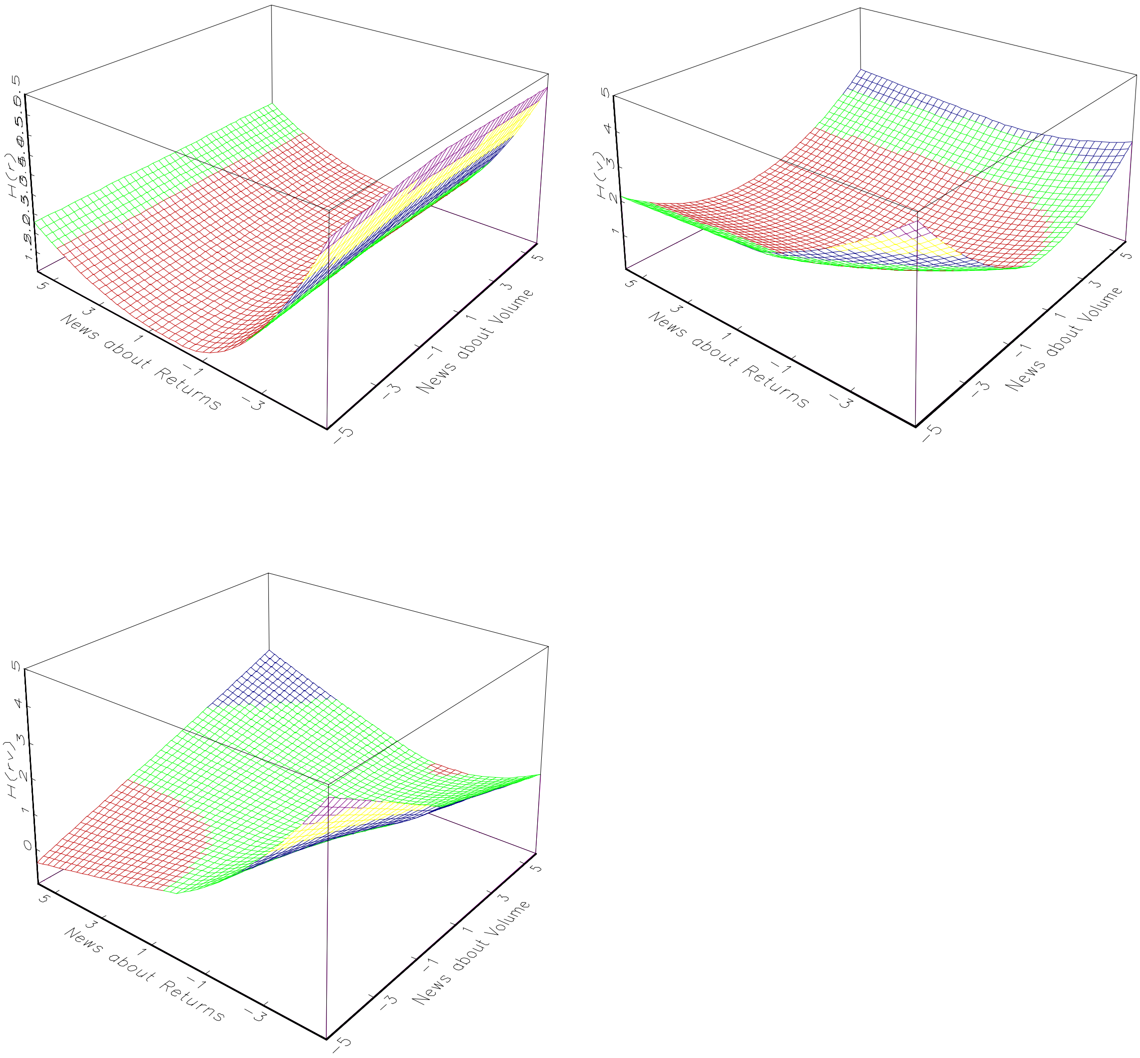


Figure 4: News Impact Surfaces : HSBC - Short Sales

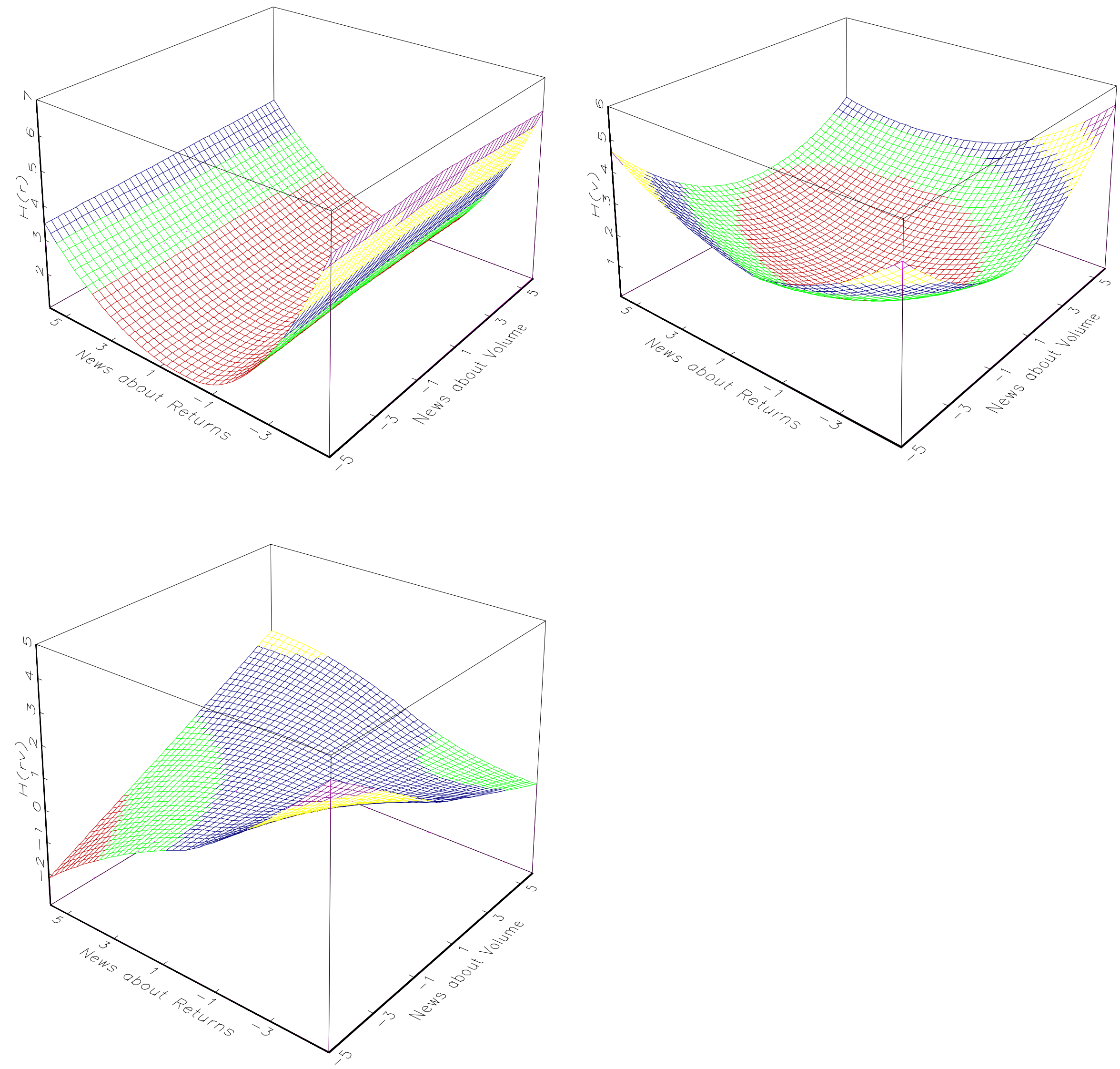


Figure 5: News Impact Surfaces : HK&C Gas - No Short Sales

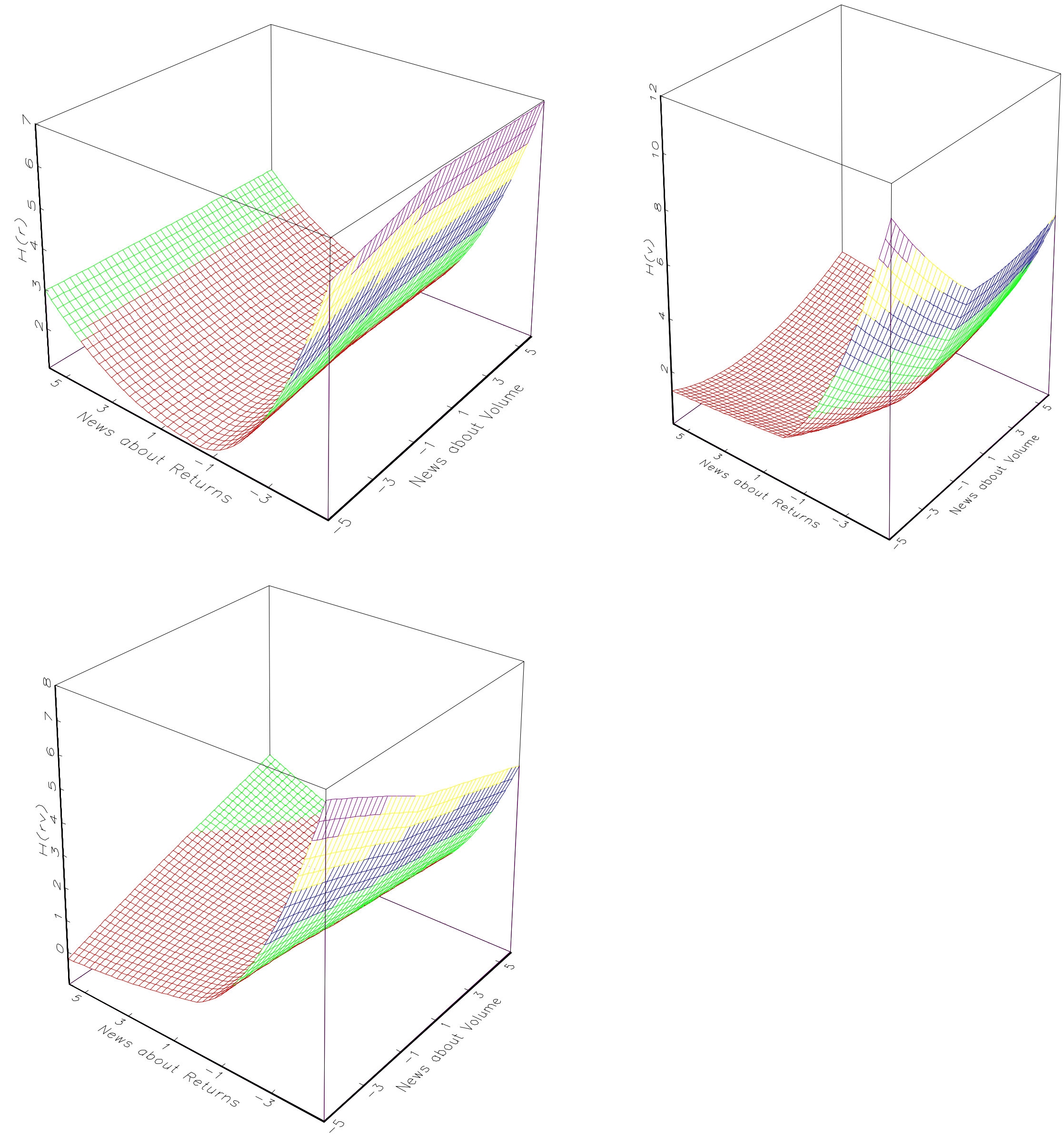


Figure 6: News Impact Surfaces : HK&C Gas - Short Sales

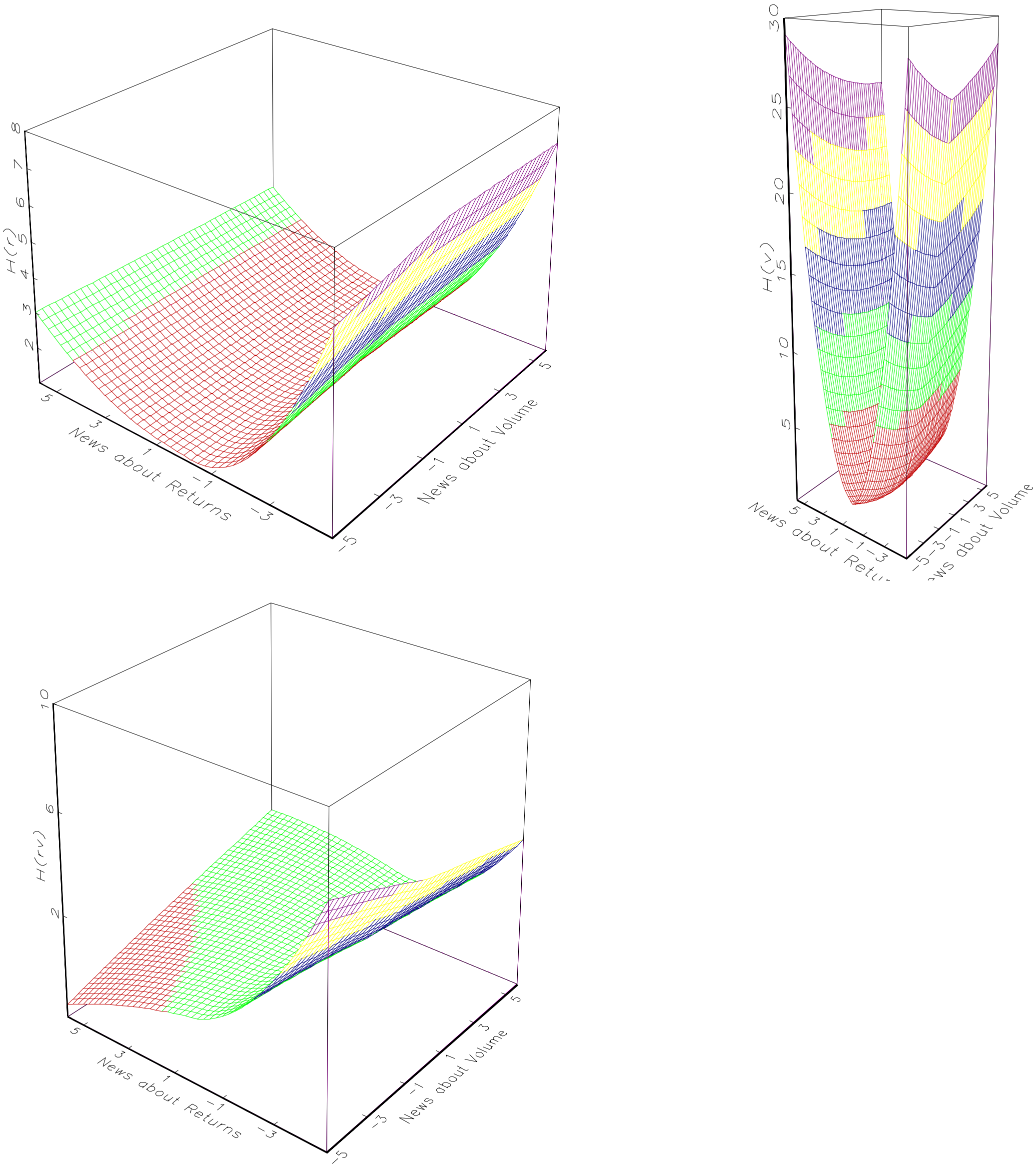


Figure 7: News Impact Surfaces Henderson - No Short Sales

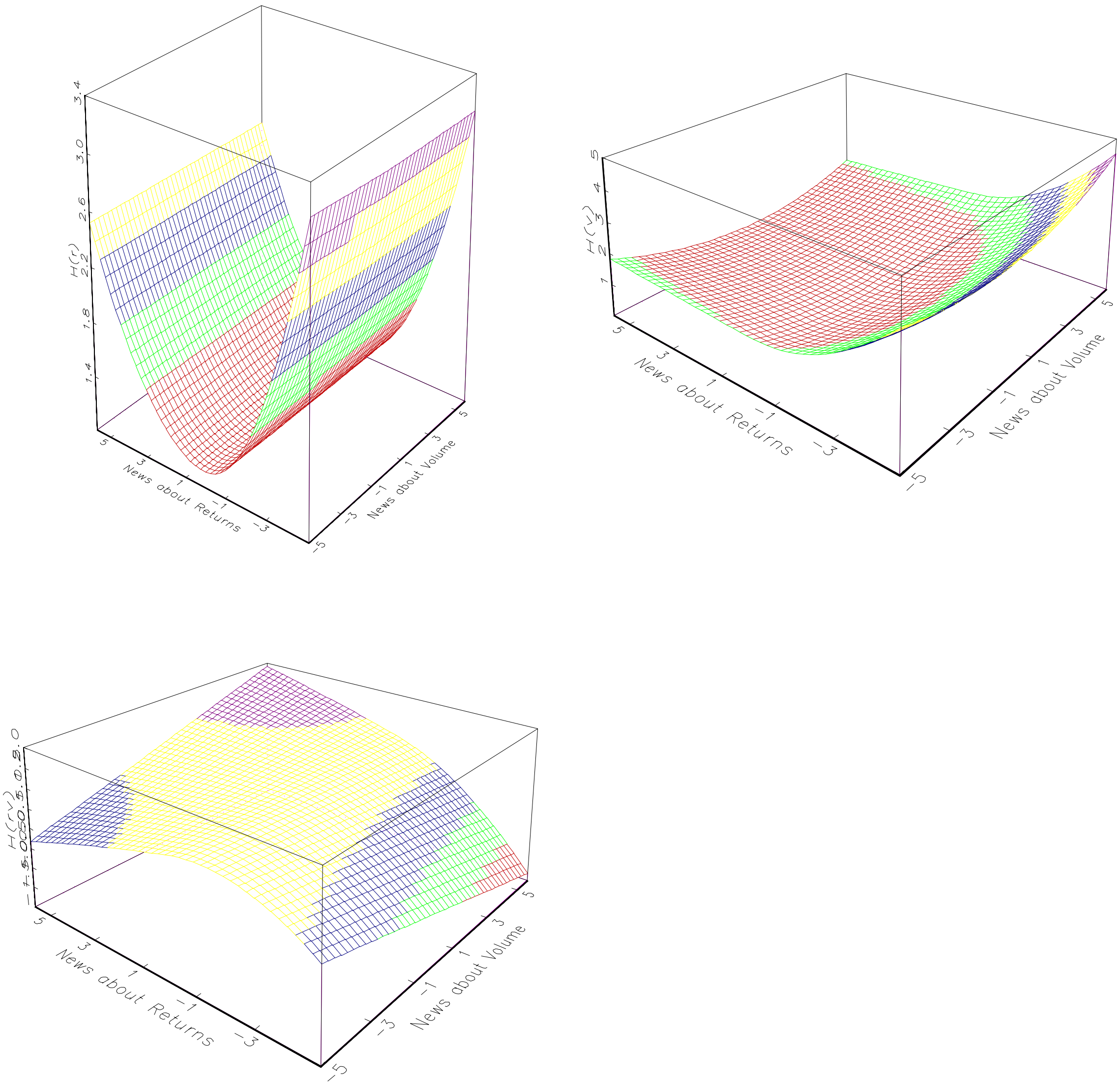


Figure 8: News Impact Surfaces : Henderson - Short Sales

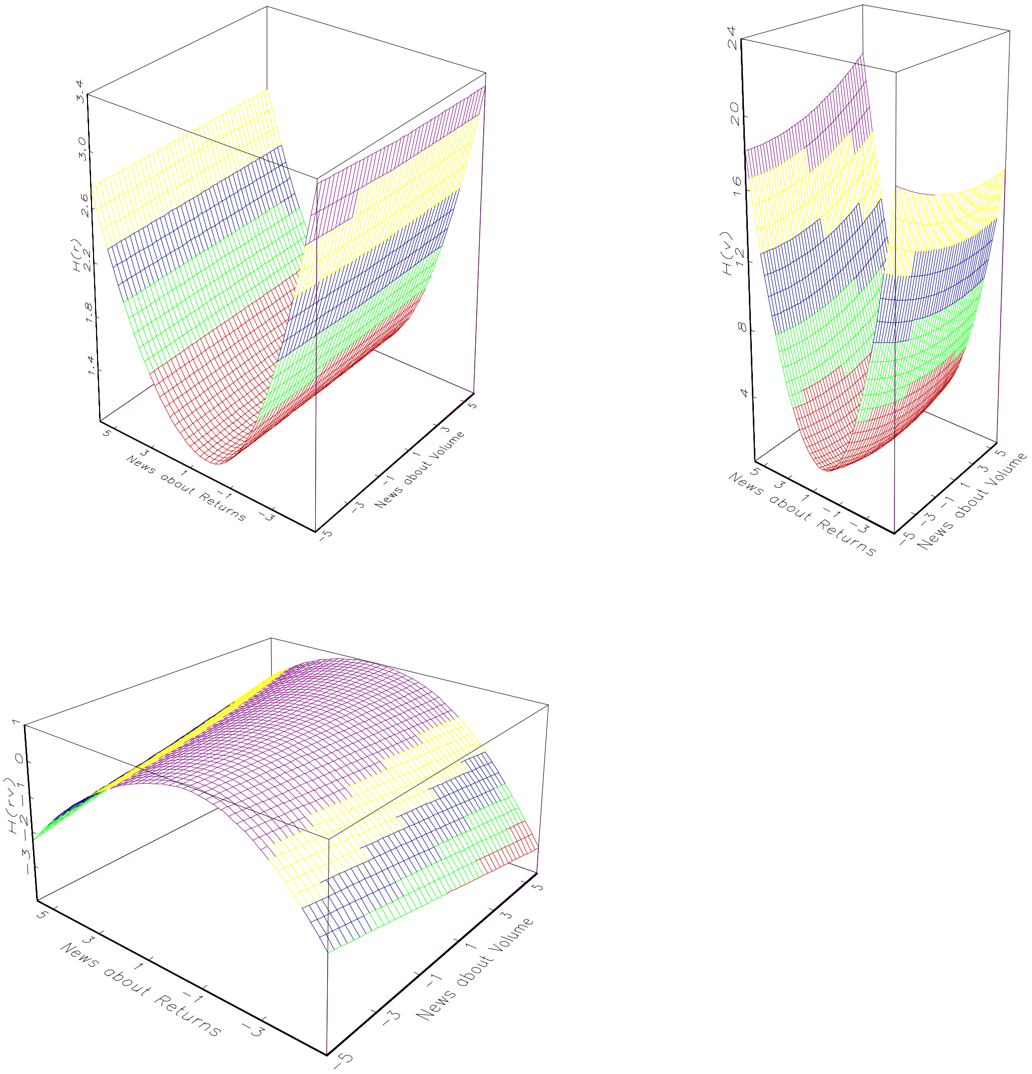


Figure 9: News Impact Surfaces : Hutchison -No Short Sales

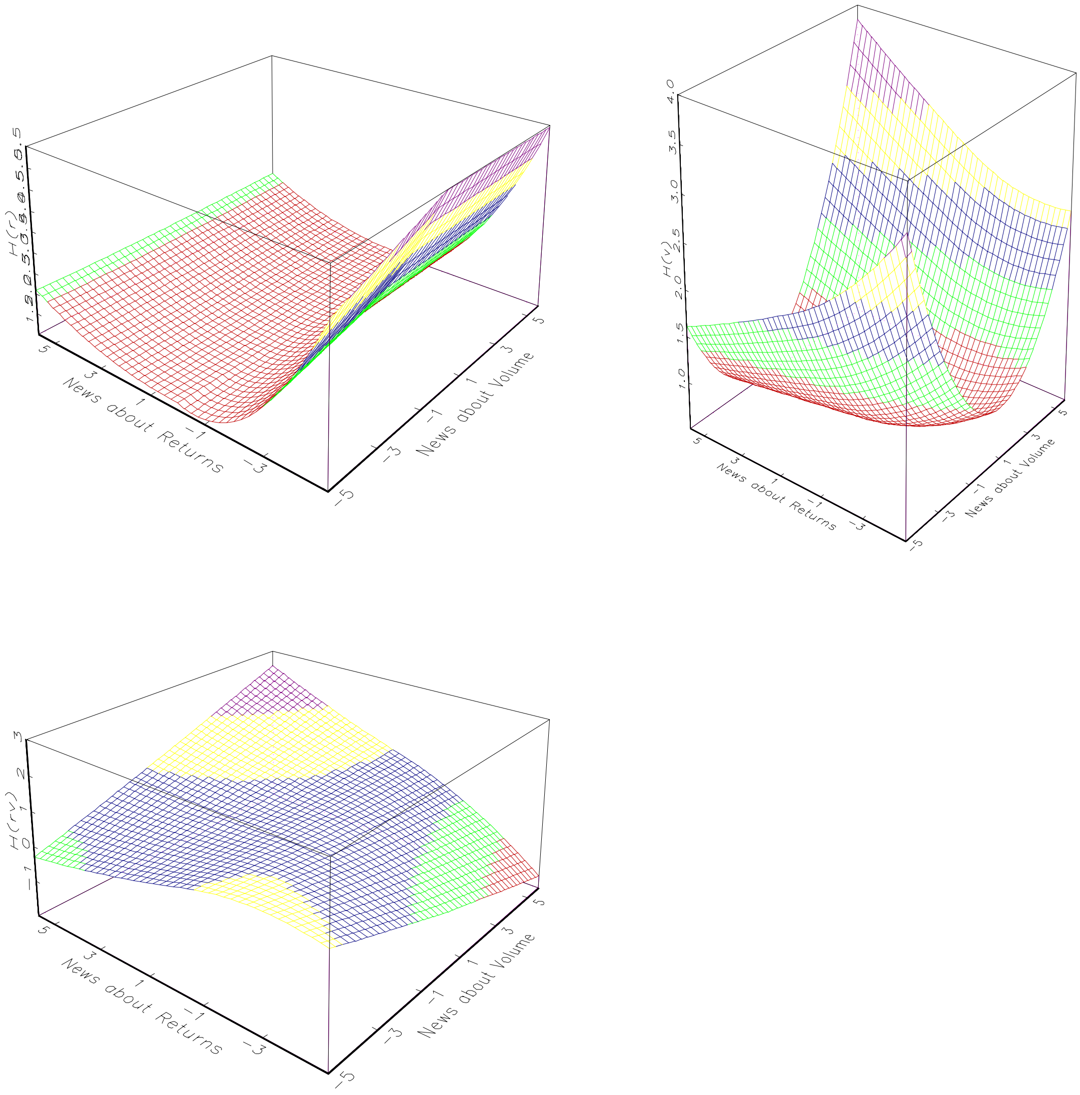


Figure 10: News Impact Surfaces : Hutchison - Short Sales

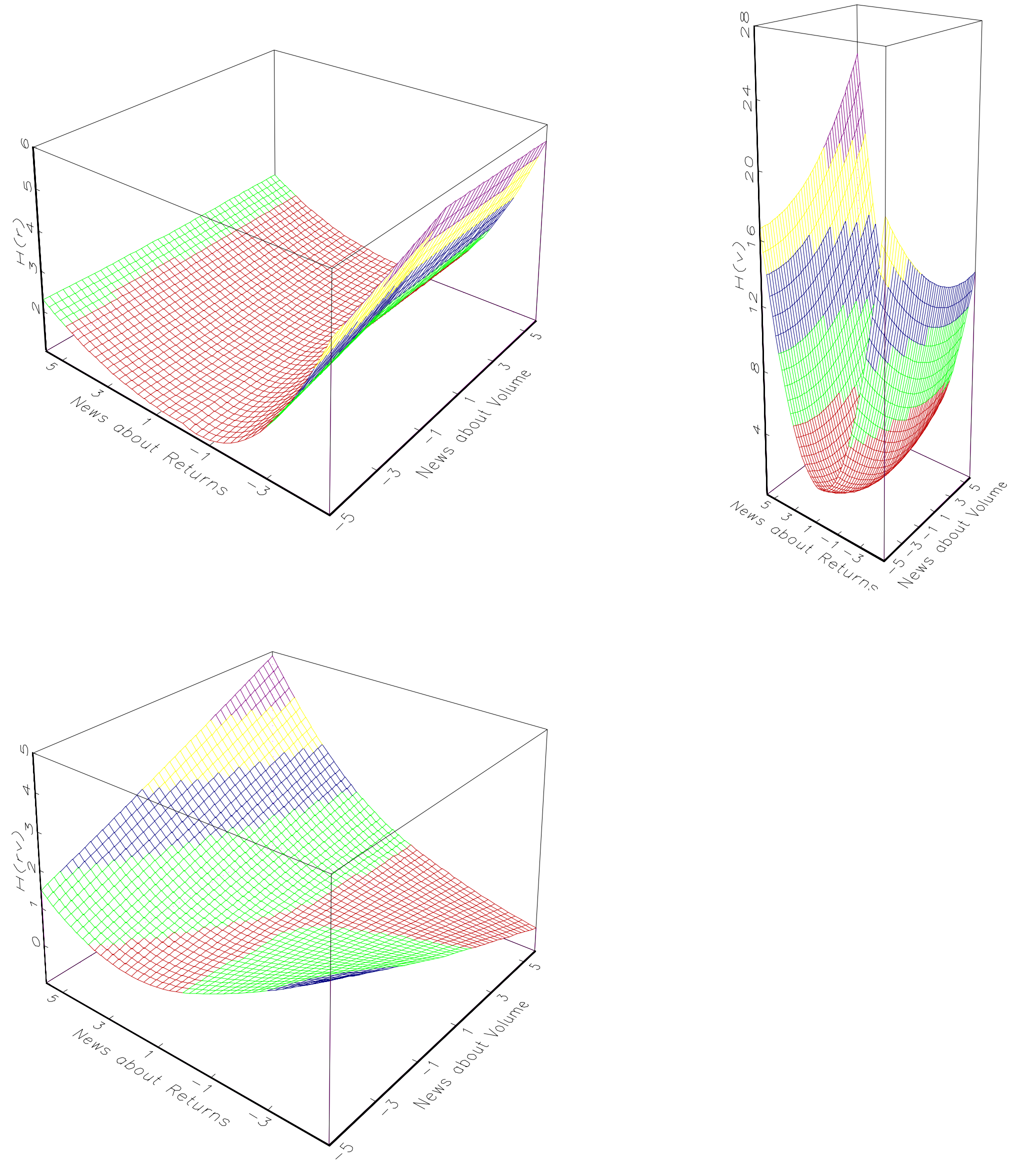
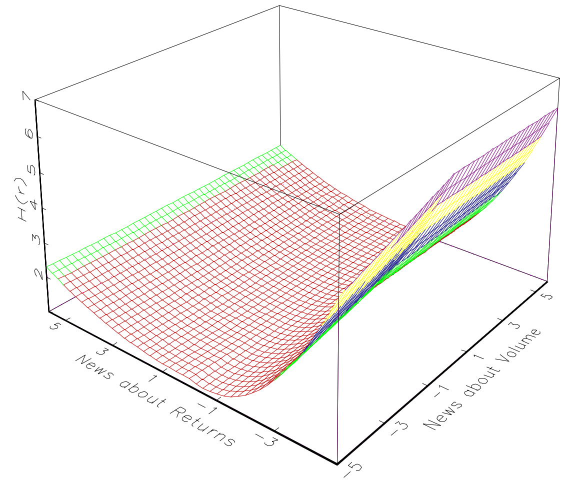
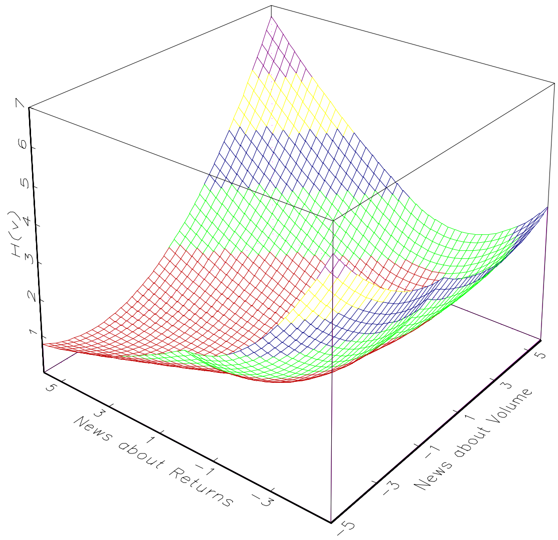


Figure 11: News Impact Surfaces : Cheung Kong - No Short Sales





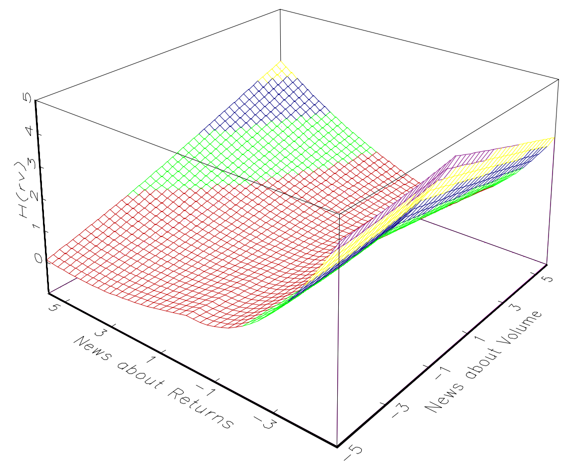


Figure 12: News Impact Surfaces : Cheung Kong - Short Sales