The Impact of News on Measures of Undiversifiable Risk: Evidence from the UK Stock Market*

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Abstract

The usual measure of the undiversifiable risk of a portfolio is its beta. Recent research has allowed beta estimates to vary over time, often based on symmetric multivariate GARCH models. There is, however, widespread evidence in the literature that the volatilities of asset returns, in particular those from stock markets, show evidence of an asymmetric response to good and bad news. Using UK equity index data,, this paper considers the impact of news on time varying measures of beta. The results suggest that beta depends on two sources of news - news about the market and news about the sector. The asymmetric effect in beta is consistent across all sectors considered. Recent research provides conflicting evidence as to whether abnormalities in equity returns are a result of changes in expected returns in an efficient market or an over-reaction to new information. The evidence in this paper suggests that such abnormalities may occur as a result of changes in expected return caused by time-variation and asymmetry in beta.

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1. Introduction

There is widespread evidence that the volatility of equity returns is higher in bull markets than in bear markets. One potential explanation for such asymmetry in variance is the so-called 'leverage effect' of Black (1976) and Christie (1982). 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 is provided by the 'volatility-feedback' hypothesis. Assuming constant dividends, if expected returns increase when stock price volatility increases, then stock prices should fall when volatility rises. Pagan and Schwert (1990), Nelson (1991), Campbell and Hentschel (1992), Engle and Ng (1993), Glosten, Jagannathan and Runkle (1993), and Henry (1998), *inter alia*, provide evidence of asymmetry in equity return volatility using univariate GARCH models. Kroner and Ng (1995), Braun, Nelson and Sunnier (1995), Henry and Sharma (1999) and Engle and Cho (1999) *inter alia* use multivariate GARCH models to capture time-variation and asymmetry in the variance-covariance structure of asset returns.

Such time-variation and asymmetry in volatility may be used to explain a time-varying and asymmetric beta. A risk averse investor will trade off higher levels of expected return for higher levels of risk. If the risk premium is increasing in volatility, and if beta is an adequate measure of the sensitivity to risk, then time-variation and asymmetry in the variance-covariance structure of returns may lead to time-variation and asymmetry in beta.

Recent research by Braun, Nelson and Sunnier (1995), hereafter BNS, explores time variation and asymmetry in beta using a bivariate EGARCH model. Engle and Cho (1999), hereafter EC, extend the BNS paper in two main directions. First, EC consider the differing roles of market- and asset-specific shocks. This is important since a series of negative returns caused by market or asset-specific shocks may lead to an increase in beta. Second, EC use daily data on individual firms, rather than the aggregated data used by BNS.

Our approach differs markedly from that of both BNS and EC. In particular we use a linear as opposed to an exponential multivariate GARCH model to distinguish between the role of idiosyncratic and market shocks in determining potential asymmetry in beta. The exponential GARCH approach of BNS does not readily admit negative covariance estimates, and moreover, the EGARCH form appears to dramatically overstate the response of the conditional variance to a negative shock - see Engle and Ng (1993), and Henry (1998) *inter alia*. Our approach allows for a (potentially negative) time varying and asymmetric covariance between the risky asset and market portfolio, while guaranteeing a positive definite variance-covariance matrix. Moreover we define the Conditional Beta Surface, an extension of the News Impact Surface concept of Ng and Kroner (1995). Using this approach it is possible to produce a graphical representation of the impact of idiosyncratic and market-wide shocks upon estimates of beta. We also employ indicator dummy regressions to identify sources of the observed asymmetry in the estimated beta series.

The remainder of the paper develops as follows. Section 2 outlines the strategy employed for modelling the time-variation and asymmetry in beta, while section 3 describes the data and presents the empirical results. The statistical properties of the estimated beta series are reported in section 4. The final section of the paper provides a summary and some concluding comments.

2. Modelling Time Variation and Asymmetry in Beta

The static Capital Asset Pricing Model (CAPM) predicts that the expected return to investing in a risky asset or portfolio, E($R_{S,t}$), should equal, r_f, the risk free rate of return, plus a risk premium. The risk premium is determined by a price of risk, the excepted return on the market portfolio in excess of r_f, and a quantity of risk, known as the 'beta' of asset *S*, β_S. The static CAPM may be written as

$$E(R_S) = r_f + [E(R_M) - r_f]\beta_S \tag{1}$$

where $\beta_S = \sigma_{S,M} / \sigma_M^2$. By definition $\beta_M = 1$, so portfolios with a beta greater than unity are seen as being relatively risky. Estimates of β_S may be obtained from OLS estimates of the slope coefficient in

$$R_{i,t} = b_0 + b_1 R_{M,t} + u_t \tag{2}$$

It has long been recognised that the volatility of asset returns is clustered. Thus the assumption of constant variance (let alone covariance) underlying the estimation of (2) must be regarded as tenuous. Bollerslev Engle and Wooldridge (1988), Braun, Nelson and Sunier (1995) and Engle and Cho (1999), *inter alia*, report evidence of time variation in β_S based upon the GARCH class of models. Braun, Nelson and Sunnier (1995) and Engle and Cho (1999) use the bivariate EGARCH approach specifying the conditional mean equations as

$$\begin{aligned} R_{M,t} &= h_{M,t}.z_{M,t} \\ R_{S,t} &= \beta_{S,t} R_{M,t} + h_{S,t} z_{S,t} \end{aligned} \tag{3}$$

β_S, the measure of undiversifiable risk associated with industry sector *S*, is defined as:

$$\beta_{S,t} = \frac{E_{t-1}[R_{M,t} \cdot R_{S,t}]}{E_{t-1}[R_{M,t}^2]} \tag{4}$$

where $E_{t-1}[.]$ denotes the expectation at time *t*-1. The model is completed by the equations defining the time series behaviour of $h_{M,t}, h_{S,t}$ and $\beta_{S,t}$

$$\begin{aligned} \ln(h_{M,t}) &= \varpi_M + \phi_M \left[\ln(h_{M,t-1}) - \varpi_M\right] + \gamma_M z_{M,t-1} + \lambda_M g_m(z_{M,t-1}) \\ \ln(h_{S,t}) &= \varpi_S + \phi_S \left[\ln(h_{S,t-1}) - \varpi_S\right] + \gamma_S z_{S,t-1} + \lambda_S g_S(z_{S,t-1}) + \lambda_{S,M} g_m(z_{M,t-1}) \\ \beta_S &= \xi_0 + \xi_4 \left[\beta_{S,t-1} - \xi_0\right] + \xi_1 z_{M,t-1} z_{S,t-1} + \xi_2 z_{M,t-1} + \xi_3 z_{S,t-1} \end{aligned} \tag{5}$$

where $z_{M,t}$ and $z_{S,t}$ are contemporaneously uncorrelated *i.i.d*. processes with zero mean and unit variance and $g_i(z_{I,t-1}) = \left[\left|z_{i,t-1}\right| - E\left|z_{i,t-1}\right|\right]$ for *i = M, S.*

As noted by Braun *et al.* (1995), the bivariate EGARCH (5) implies some strong assumptions. First, the model does not allow for feedback, as would be the case if

$\ln(h_{M,t}), \ln(h_{S,t})$ and $\beta_{S,t}$ followed a VARMA process. Second, the model assumes a linear autoregressive process for β_S. Third, although the model allows for leverage effects, it does so in an ad-hoc fashion.

In contrast to Braun, Nelson and Sunnier (1995), and Engle and Cho (1999), our approach allows for feedback between the conditional means and variances of $R_{M,t}$ and $R_{S,t}$. Furthermore, we make no formal assumptions as to the time series process underlying β_S. We assume a VARMA process for the returns and model the time variation in the variance-covariance matrix using a linear as opposed to an exponential GARCH model. The multivariate GARCH approach allows the researcher to examine the effects of shocks to the entire variance-covariance matrix. Thus the effect of a shock to $R_{M,t}$ on the covariance between $R_{M,t}$ and $R_{S,t}$ may be inferred directly from the parameter estimates. Moreover, the conditional variance-covariance matrix may be parameterised to be time varying and asymmetric. Given the role of covariances in asset pricing and financial risk management, correct specification of the variance-covariance structure is of paramount. For example, the conditional covariance may be used in the calculation of prices for options involving more than one underlying asset (such as rainbow options), and is vital to the calculation of minimum capital risk requirements. Both variance and covariance estimates may be used in the calculation of the measure of undiversifiable risk from the Capital Asset Pricing Model. It follows that if the variance and/or covariance terms are time-varying (and asymmetric), the CAPM β is also likely to be time-varying (and asymmetric).

The conditional mean equations of the model are specified in our study as a Vector Autoregressive Moving Average (VARMA) which may be written as:

$$\Delta Y_t = \mu + \sum_{j=1}^{m} \Gamma_j \Delta Y_{t-j} + \sum_{k=1}^{n} \Theta_k \varepsilon_{t-k} + \varepsilon_t$$
$$Y_t = \begin{bmatrix} R_{M,t} \\ R_{S,t} \end{bmatrix}; \mu = \begin{bmatrix} \mu_M \\ \mu_S \end{bmatrix}; \Gamma_j = \begin{bmatrix} \Gamma_{j,M}^{(M)} & \Gamma_{j,S}^{(S)} \\ \Gamma_{j,M}^{(i)} & \Gamma_{j,S}^{(S)} \end{bmatrix}; \Theta_k = \begin{bmatrix} \Theta_{k,M}^{(M)} & \Theta_{k,S}^{(M)} \\ \Theta_{k,M}^{(S)} & \Theta_{k,S}^{(S)} \end{bmatrix}; \varepsilon_t = \begin{bmatrix} \varepsilon_{M,t} \\ \varepsilon_{S,t} \end{bmatrix} \quad (6)$$

where *M* and *S* denote the market and sector respectively. [1]

Under the assumption $\varepsilon_t \mid \Omega_t \sim (0, H_t)$, where ε_t represents the innovation vector in (6) and defining h_t as $vec(H_t)$, where *vec* is the operator that stacks the columns of a matrix, the bivariate VARMA(m,n) GARCH(1,1) *vec* model may be written

$$vec(H_t) = h_t = \begin{bmatrix} h_{M,t} \\ h_{MS,t} \\ h_{S,t} \end{bmatrix} = C_0 + A_1 vec(\varepsilon_{t-1}\varepsilon_{t-1}') + B_1 h_{t-1} \qquad (7)$$

where

$$C_0 = \begin{bmatrix} c_{11} \\ c_{12} \\ c_{22} \end{bmatrix}; \quad A_1 = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}; \; B_1 = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}$$

Restricting the matrices A_1 and B_1 to be diagonal gives the model proposed by Bollerslev, Engle and Wooldridge (1988) where each element of the conditional variance-covariance matrix, $H_{,t}$, depends on past values of itself and past values of $\varepsilon_{t-1}\varepsilon_{t-1}'$. There are 21 free parameters in the conditional variance-covariance structure of the bivariate *GARCH*(1,1) *vec* model (7) to be estimated, subject to the requirement that H_t be positive definite for all values of ε_t in the sample. The difficulty of checking, let alone imposing such a restriction led Engle and Kroner (1995) to propose the *BEKK* parameterisation

$$H_t = C_0^{*\prime} C_0^* + A_{11}^{*\prime} H_{t-1} A_{11}^* + B_{11}^{*\prime} \varepsilon_{t-1}\varepsilon_{t-1}' B_{11}^* \qquad (8)$$

The BEKK parameterisation requires estimation of only 11 free parameters in the conditional variance-covariance structure and guarantees H_t positive definite. It is important to note that the BEKK and *vec* models imply that only the magnitude of past return innovations is important in determining current conditional variances and covariances. This assumption of symmetric time-varying variance-covariance matrices must be considered tenuous given 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, and Kroner and Ng, 1996, *inter alia*).

Defining $\xi_{j,t} = \min\{\varepsilon_t, 0\}$ for *j* = *market*, *sector*, the BEKK model in (8) may be extended to allow for asymmetric responses as

$$H_t = C_0^{*'} C_0^* + A_{11}^{*'} H_{t-1} A_{11}^* + B_{11}^{*'} \varepsilon_{t-1} \varepsilon_{t-1}^{'} B_{11}^* + D_{11}^{*'} \xi_{t-1} \xi_{t-1}^{'} D_{11}^* \qquad (9)$$

where

$$C_0^* = \begin{bmatrix} c_{11}^* & c_{12}^* \\ 0 & c_{22}^* \end{bmatrix}; \qquad A_{11}^* = \begin{bmatrix} a_{11}^* & a_{12}^* \\ a_{21}^* & a_{22}^* \end{bmatrix}; \qquad B_{11}^* = \begin{bmatrix} b_{11}^* & b_{12}^* \\ b_{21}^* & b_{22}^* \end{bmatrix}; \qquad D_{11}^* = \begin{bmatrix} d_{11}^* & d_{12}^* \\ d_{21}^* & d_{22}^* \end{bmatrix} \quad \text{and} \quad \xi_t^2 = \begin{bmatrix} \xi_{M,t}^2 \\ \xi_{S,t}^2 \end{bmatrix} \qquad (10)$$

The symmetric *BEKK* model (8) is given as a special case of (9) for $d_{i,j}^* = 0$, for all values of *i* and *j*. Given estimates of $H_{MS,t}$, the conditional covariance between the return to the market portfolio, $R_{M,t}$, and the return to the individual sector, $R_{S,t}$, and the variance of return to the market portfolio, $H_{M,t}$, it is possible to calculate a time varying estimate of β_S, the measure of undiversifiable risk associated with industry sector *S* as:

$$\beta_{S,t} = \frac{H_{MS,t}}{H_{M,t}} = \frac{E_{t-1}[R_{M,t} \cdot R_{S,t}]}{E_{t-1}[R_{M,t}^2]} \qquad (11)$$

where $E_{t-1}[.]$ denotes the expectation at time *t*-1.

Kroner and Ng (1996) 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 $h_{M,t}(h_{S,t})$, the conditional variance of $R_{M,t}(R_{S,t})$, is affected by the sign of the innovation in $R_{M,t}(R_{S,t})$. Second, the covariance matrix displays *cross variance asymmetry* if the conditional variance of $R_{M,t}(R_{S,t})$ is affected by the sign of the innovation in $R_{S,t}(R_{M,t})$. Finally, if the covariance of returns $h_{MS,t}$ is sensitive to the sign of the innovation in return for either portfolio, the model is said to display *covariance asymmetry*.

The innovation in prices from time *t-1* to time *t*, $P_t - P_{t-1} = \varepsilon_t$, represents changes in information available to the market (*ceteris paribus*). Kroner and Ng (1996) treat such innovations as a collective measure of news arriving to market *j* between the close of trade on period *t-1* and the close of trade on period *t*. Kroner and Ng (1996) define the relationship between innovations in return and the conditional variance-covariance structure as the news impact surface, a multivariate form of the news impact curve of Engle and Ng (1993). By construction, the model allows β_S, the measure of undiversifiable risk associated with industry sector *S* to respond asymmetrically to news about the market portfolio and/or news about sector *S*.

3. Data Descriptions and Empirical Results

Weekly UK equity index data for the period 01/01/1965 to 01/12/1999 was obtained from Datastream International. The FT-All Shares index was used as a proxy for the market portfolio. The paper considers six Industry sector return indices, namely Basic Industries (BASICUK), Total Financials (TOTLFUK), Healthcare, (HLTHCUK), Publishing (PUBLSUK), Retail (RTAILUK) and Real Estate, (RLESTUK). In all cases the data was in accumulation index form and was transformed into continuously compounded returns for sector *i* as

$$R_{i,t} = 100 \times \ln(P_{i,t} / P_{i,t-1}) \tag{12}$$

Summary statistics for the data are presented in table 1. As one might anticipate, the data display evidence of extreme non-normality. In only one case, Healthcare, is the degree of skewness not statistically significant. In all cases the data display strong evidence of excess kurtosis. Columns 1 and 2 of Figure 1 display the index and returns data respectively. Visual inspection of the graph of the returns data suggests that there is strong volatility clustering. A Ljung-Box test on the squared return data suggests that there is strong evidence of Autoregressive Conditional Heteroscedasticity (ARCH) in the data. The final column of table

1 displays static estimates of undiversifiable risk obtained from OLS estimation of (2). The range of estimates runs from 0.930 for Health Care to 1.079 for Retailing.

The Akaike and Schwarz Information criteria were used to determine the lag order of the VARMA model (6). In all cases, the restricted VARMA(2,1) given as (12) was deemed optimal:

$$\Delta Y_t = \mu + \sum_{j=1}^{2} \Gamma_j \Delta Y_{t-j} + \Theta_1 \varepsilon_{t-1} + \varepsilon_t$$

$$Y_t = \begin{bmatrix} R_{M,t} \\ R_{S,t} \end{bmatrix}; \mu = \begin{bmatrix} \mu_M \\ \mu_S \end{bmatrix}; \Gamma_j = \begin{bmatrix} \Gamma_{j,M}^{(M)} & \Gamma_{j,S}^{(S)} \\ \Gamma_{j,M}^{(i)} & \Gamma_{j,S}^{(S)} \end{bmatrix}; \Theta_k = \begin{bmatrix} \Theta_{k,M}^{(M)} & 0 \\ 0 & \Theta_{k,S}^{(S)} \end{bmatrix}; \varepsilon_t = \begin{bmatrix} \varepsilon_{M,t} \\ \varepsilon_{S,t} \end{bmatrix} \quad (12)$$

Maximum likelihood techniques were used to obtain estimates of parameters for equations (9) and (12) assuming a Student's-*t* distribution with unknown degrees of freedom for the errors. The parameter estimates for the conditional mean and variance equations are displayed in Tables 2a and 2b respectively. Shocks to volatility appear highly persistent. Estimates of the main diagonal elements of A_{11}^* are, in general, close to unity. There is strong evidence of own variance, cross variance and covariance asymmetry in the data. This is highlighted by the significance of the parameters in the D_{11}^* matrix. The insignificance of the off-diagonal elements in the B_{11}^* matrix suggests that the majority of important volatility spillovers from the market to the sector are associated with negative realisations of $R_{M,t}$. With the exception of the financial sector, the models all pass the usual Ljung-Box test for serial correlation in the standardised and squared standardised residuals displayed in table 3.

Figures 2-7 display the variance and covariance news impact surfaces for the estimates of the Multivariate GARCH model displayed in Table 2. Following Engle and Ng (1993) and Ng and Kroner (1996), each surface is evaluated in the region $\varepsilon_{j,t} = [-5,5]$ for *j = Market, Sector,* holding information at time *t-1* and before constant. There are relatively few extreme outliers in the data, which suggests that some caution should be exercised in interpreting the news impact surfaces for larger absolute values of $\varepsilon_{j,t}$. Despite this caveat, the asymmetry in variance and covariance is clear from each figure. The sign and magnitude of idiosyncratic and market shocks have clearly differing impacts on elements of H_t. In the cases of the basic industries, retail and healthcare sectors, a market-wide shock has a bigger impact on subsequent volatility than an idiosyncratic shock of the same size. In fact, an idiosyncratic shock has virtually no effect on volatility since that part of the surface on the first diagram is flat. On the other hand, in the cases of the financial and real estate sectors, idiosyncratic socks have a much stronger role to play.

Holding information at time *t-1* and before constant, and evaluating $\beta_{S,t}$ in the range $\varepsilon_{j,t} = [-5,5]$ for *j* = *Market, Sector* as before yields the response of the measure of undiversifiable risk to news. The fourth panel of figures 2-7 graphs the response of $\beta_{S,t}$ to news using the estimates displayed in Table 2. Again, the asymmetry in response to market and idiosyncratic shocks is clear.

4. Properties of the $\hat{\beta}_{S,t}$ series

The third column of Figure 1 plots the estimated $\hat{\beta}_{S,t}$. The time variation of the measure of undiversifiable risk across each sector is evident. Table 3 presents descriptive statistics for the $\hat{\beta}_{S,t}$ series. The most volatile of the $\hat{\beta}_{S,t}$ series is associated with the healthcare industry. Here the $\hat{\beta}_{S,t}$ ranges from a minimum of 0.53 to a maximum of 2.09. In terms of the average value of $\hat{\beta}_{S,t}$, retailing appears to be the riskiest sector, with a $\hat{\beta}_{S,t}$=1.15, indicating that retailing has higher risk than the market portfolio which has $\beta_{M,t} = 1$ by definition. The averages of the $\hat{\beta}_{S,t}$ compare favourably with the static estimates presented in table 1. On the basis of a sequence of Dickey-Fuller unit root tests, the $\hat{\beta}_{S,t}$ series appear stationary.

What factors underlay the observed asymmetry in $\hat{\beta}_{S,t}$? EC argue that shocks to the market and idiosyncratic shocks determine asymmetric effects in $\hat{\beta}_{S,t}$. This logic underlies the News Impact Surface that we propose for $\hat{\beta}_{S,t}$ depicted in Figures 2 to 6. To identify negative returns to the market, let $I_{M,t}$ represent an indicator variable, which takes the value of unity when $R_{M,t}$, the return to the market portfolio, is negative and zero otherwise. Similarly, in order to identify the magnitude of negative market returns, let $R^{-}_{M,t} = I_{M,t} \times R_{M,t}$. Similar variables may be defined to identify negative return innovations and the corresponding magnitudes for each individual sector.

Consider the OLS regression

$$\hat{\beta}_{S,t} = \phi_1 + \phi_2 I_{M,t} + \phi_3 R^{-}_{M,t} + \phi_4 I_{S,t} + \phi_5 R^{-}_{S,t} + \phi_6 C_{S,t} + \phi_7 C_{M,t} + u_t \qquad (13)$$

where $C_{S,t} = I_{M,t} \times R_{S,t}$, and $C_{M,t} = I_{S,t} \times R_{M,t}$ represent dummy variables designed to capture the sector return when the market return is negative ($C_{S,t}$) and the market return when the sector return is negative ($C_{M,t}$).

The results from estimation of (13) are displayed in table 4. Periods of negative returns to the market only significantly affect $\hat{\beta}_{S,t}$ for the health and publishing sectors, in both cases leading to a fall in the value of the measure of undiversifiable risk. However, large negative innovations to the market portfolio uniformly lead to an increase in $\hat{\beta}_{S,t}$ across all sectors considered. There is no pattern of correlation between a negative return to the sector and changes in $\hat{\beta}_{S,t}$. Similarly, $C_{S,t}$ and $C_{M,t}$ do not appear to significantly affect estimates of systematic risk.

5. Summary and Conclusions

Recent research provides conflicting evidence as to whether abnormalities in equity returns are a result of changes in expected returns in an efficient market or an over-reaction to new information in a market that is inefficient. De Bondt and Thaler (1985), Chopra, Lakonishok and Ritter (1992), and Jegadeesh and Titman (1993) *inter alia*, conclude that the return to a portfolio formed by buying stocks which have suffered capital losses (*losers*) in the past, and selling stocks which have experienced capital gains (*winners*) in the past, has a higher average return that predicted by the CAPM. All three studies conclude that such over-reaction is inconsistent with efficiency, since such contrarian strategies should not consistently earn excess returns.

On the other hand, Chan (1988), and Ball and Kothari (1989) argue that the time variation in expected return due to time-variation in beta can explain the success of the 'losers' portfolio. The studies find that there exists predictive asymmetry in the response of the conditional beta to large positive and negative innovations. Braun, Nelson and Sunier (1995) find weak evidence of asymmetry in beta, but conclude that it is not sufficient to explain the over-reaction to information, or mean reversion in stock prices. Engle and Cho (1999) argue that this lack of evidence of asymmetry in beta is due to stock price aggregration and lack of cross-sectional variation in the monthly data used by Braun, Nelson and Sunier (1995). Engle and Cho (1999) argue that the use of daily data on individual stocks makes the detection of asymmetry an easier task.

This paper employs weekly data on industry sectors from the UK equity market to examine the impact of news on time-varying measures of beta. The use of weekly data on sectors of the market should overcome the potential price aggregation problems associated with lower frequency data, and maintain sufficient cross-sectional variation to detect time variation and asymmetry in beta.

Treating prices innovations as a collective measure of news arriving to the market between time $t-1$ and time t, the results suggest that time-variation in beta depends on two sources of news - news about the market and news about the sector. However, the asymmetric response of beta to news appears related only to large negative innovations to the market. Bad news about each individual sector does not appear to significantly affect the measure of undiversifiable risk. The asymmetric effect in beta is consistent across all sectors considered.

Given the magnitude of the asymmetry identified in beta, the evidence in this paper suggests that abnormalities such as mean reversion in stock prices may occur as a result of changes in expected return caused by time-variation and asymmetry in beta, rather than as a by-product of market inefficiency.

Footnotes

[1]We also considered GARCH-M versions of (6). However, on the basis of Wald and LR tests, the VARMA-GARCH was chosen as the optimal conditional data characterisation.

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Tables and Figures

Table 1: Summary statistics for the returns data

Series	Mean	Variance	Skew	E.K.	ρ_1	Q(5)	$Q^2(5)$	β
FTALL	0.280	6.288	-0.323	9.082	0.071	56.67	231.036	1.00
			[0.000]	[0.000]		[0.000]	[0.000]	
BASIC	0.226	7.690	-0.517	7.975	0.079	44.447	55.825	0.976
			[0.000]	[0.000]		[0.000]	[0.000]	(0.012)
TOTLF	0.303	7.260	0.007	6.941	0.111	56.668	342.389	0.978
			[0.900]	[0.000]		[0.000]	[0.000]	(0.010)
HLTH	0.280	10.842	-0.061	5.459	0.016	21.715	155.245	0.930
			[0.290]	[0.000]		[0.001]	[0.000]	(0.022)
PUBLS	0.245	9.883	-0.650	10.531	0.107	48.013	107.912	1.040
			[0.000]	[0.000]		[0.000]	[0.000]	(0.016)
RTAIL	0.256	11.129	0.168	3.737	0.002	6.009	122.797	1.079
			[0.000]	[0.000]		[0.305]	[0.000]	(0.018)
RLEST	0.249	11.908	-0.159	6.579	0.097	33.713	391.338	1.032
			[0.000]	[0.000]		[0.000]	[0.000]	(0.021)

Notes to Table 1: Marginal significance levels displayed as [.], standard errors displayed as (.). Skew measures the third moment of the distribution and reports the marginal significance of a test for zero skewness. E.K. reports the excess kurtosis of the return distribution and the associated marginal significance level for the test of zero excess kurtosis. The first order autocorrelation coefficient is ρ_1. Q(5) and $Q^2(5)$ are Ljung-Box tests for fifth order serial correlation in the returns and the squared returns, respectively. Both tests are distributed as $\chi^2(5)$ under the null. β is the OLS estimate of the measure of undiversifiable risk.

Table 2a: Conditional Mean Estimates

	BASIC	TOTLF	HLTH	PUBLS	RTAIL	RLEST
$\mu^{(M)}$	0.338	0.244	0.224	0.0293	0.222	0.268
	(0.027)	(0.020)	(0.032)	(0.0300)	(0.032)	(0.032)
$\Gamma_{1,M}^{(M)}$	-0.255	-0.010	0.195	-0.104	0.145	-0.011
	(0.031)	(0.009)	(0.021)	(0.014)	(0.018)	(0.016)
$\Gamma_{2,M}^{(M)}$	0.013	0.044	0.044	0.127	0.150	0.083
	(0.019)	(0.009)	(0.014)	(0.012)	(0.014)	(0.013)
$\Gamma_{1,S}^{(M)}$	0.045	0.043	0.005	0.038	0.035	0.013
	(0.020)	(0.009)	(0.012)	(0.010)	(0.010)	(0.011)
$\Gamma_{2,S}^{(M)}$	0.002	0.074	0.062	-0.001	-0.026	0.024
	(0.015)	(0.009)	(0.011)	(0.012)	(0.010)	(0.010)
$\Theta_{1,M}^{(M)}$	0.252	-0.016	-0.018	0.100	-0.178	0.029
	(0.053)	(0.010)	(0.019)	(0.013)	(0.017)	(0.015)
$\mu^{(S)}$	0.199	0.268	0.263	0.224	0.276	0.221
	(0.029)	(0.022)	(0.051)	(0.037)	(0.052)	(0.045)
$\Gamma_{1,M}^{(S)}$	-0.011	0.004	0.113	0.048	-0.021	0.002
	(0.032)	(0.010)	(0.019)	(0.017)	(0.019)	(0.019)
$\Gamma_{2,M}^{(S)}$	0.103	0.021	0.088	0.202	0.164	0.031
	(0.015)	(0.010)	(0.019)	(0.016)	(0.021)	(0.017)
$\Gamma_{1,S}^{(S)}$	0.040	0.029	-0.078	0.053	-0.065	0.101
	(0.048)	(0.011)	(0.013)	(0.014)	(0.012)	(0.013)
$\Gamma_{2,S}^{(S)}$	0.013	0.090	0.004	-0.047	-0.072	0.009
	(0.017)	(0.009)	(0.014)	(0.013	(0.015)	(0.012)
$\Theta_{1,S}^{(S)}$	0.014	0.024	0.038	-0.010	0.039	-0.018
	(0.038)	(0.011)	(0.014)	(0.016)	(0.013)	(0.012)

Notes to table 2a: Standard errors displayed as (.)

Table 2b: Conditional Variance Estimates						
	BASIC	TOTLF	HLTH	PUBLS	RTAIL	RLEST
c_{11}	0.362	0.220	0.467	0.527	0.341	0.488
	(0.060)	(0.040)	(0.064)	(0.060)	(0.041)	(0.062)
c_{12}	0.351	0.318	0.088	-0.102	0.130	0.385
	(0.078)	(0.055)	(0.068	(0.093)	(0.065)	(0.042)
c_{22}	-0.201	0.135	0.485	0.503	0.030	0.260
	(0.031)	(0.030)	(0.095)	(0.118)	(0.070)	(0.050)
a_{11}	0.955	0.982	0.903	0.796	0.904	0.919
	(0.013)	(0.008)	(0.023)	(0.030)	(0.011)	(0.022)
a_{12}	0.003	0.006	-0.043	-0.017	-0.065	-0.059
	(0.015)	(0.008)	(0.035)	(0.054)	(0.013)	(0.024)
a_{12}	-0.010	-0.023	0.032	0.138	0.037	0.011
	(0.014)	(0.009)	(0.016)	(0.028)	(0.007)	(0.017)
a_{22}	0.947	0.945	0.957	0.956	1.017	0.969
	(0.156)	(0.010)	(0.022)	(0.046)	(0.006)	(0.016)
b_{11}	0.186	0.265	0.164	0.038	0.244	0.247
	(0.044)	(0.026)	(0.051)	(0.066)	(0.031)	(0.046)
b_{12}	-0.067	0.127	0.089	0.383	0.090	0.113
	(0.048)	(0.028)	(0.062)	(0.071)	(0.039)	(0.044)
b_{21}	0.028	-0.047	0.022	0.037	-0.017	-0.043
	(0.039)	(0.023)	(0.030)	(0.052)	(0.025)	(0.033)
b_{22}	0.251	0.121	0.237	-0.108	0.086	0.174
	(0.043)	(0.031)	(0.042)	(0.059)	(0.033)	(0.035)
d_{11}	0.456	-0.020	0.405	-0.440	0.457	0.035
	(0.069)	(0.045)	(0.064)	(0.072)	(0.058)	(0.098)
d_{12}	0.397	-0.150	0.347	-0.153	0.335	0.137
	(0.082)	(0.048)	(0.109)	(0.081)	(0.062)	(0.092)
d_{21}	-0.202	0.224	-0.074	0.089	-0.247	0.207
	(0.078)	(0.043)	(0.070)	(0.059)	(0.038)	(0.064)
d_{22}	-0.114	0.357	-0.106	-0.153	-0.088	0.360
	(0.100)	(0.057)	(0.109)	(0.066)	(0.046)	(0.063)

Notes to Table 2b: Standard errors displayed as (.)

Table 2c: Residual Diagnostics						
	BASIC	TOTLF	HLTH	PUBLS	RTAIL	RLEST
η	9.479	9.162	8.169	8.059	8.217	8.752
	(0.678)	(0.583)	(0.699)	(0.613)	(0.486)	(0.254)
Log L	-4748.50	-4541.90	-5888.67	-5400.53	-5582.29	-5720.45
$Q(5)^M$	8.893	12.134	13.434	10.324	12.309	11.481
	[0.110]	[0.033]	[0.020]	[0.067]	[0.031]	[0.043]
$Q^2(5)^M$	0.767	0.764	1.069	1.383	1.844	0.536
	[0.979]	[0.979]	[0.957]	[0.926]	[0.870]	[0.991]
$Q(5)^S$	6.183	9.855	10.016	3.138	3.053	7.224
	[0.235]	[0.079]	[0.075]	[0.679]	[0.692]	[0.203]
$Q^2(5)^S$	0.781	2.933	9.7063	0.987	4.573	10.479
	[0.978]	[0.710]	[0.084]	[0.964]	[0.470]	[0.063]

Notes to Table 2c: Standard errors displayed as (.). Marginal significance levels displayed as [.].η represents the degrees of freedom parameter estimated from the students-t density. $Q(5)^i$ and $Q^2(5)^i$ represent Ljung Box tests for serial dependence in the standardised residuals and their corresponding squares for *i=Market, Sector*

Table 3: Descriptive Statistics for $\hat{\beta}_{S,t}$						
	BASIC	TOTLF	HLTH	PUBLS	RTAIL	RLEST
Mean	0.990	0.966	0.883	0.969	1.115	0.913
Variance	0.009	0.014	0.032	0.008	0.024	0.038
Skew	-0.002	0.375	1.458	0.486	-0.201	0.428
	[0.976]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
EK	0.830	0.016	6.037	1.2030	-0.348	-0.143
	[0.000]	[0.883]	[0.000]	[0.000]	[0.003]	[0.]
Min	0.653	0.597	0.530	0.666	0.617	0.459
Max	1.326	1.325	2.092	1.506	1.500	1.507
ADF	-7.007	-5.554	-7.619	-10.752	-5.938	-6.750

Notes to Table 3: Marginal significance levels displayed as [.]. Skew measures the third moment of the distribution and reports the marginal significance of a test for zero skewness. E.K. reports the excess kurtosis of the distribution and the associated marginal significance level for the test of zero excess kurtosis. ADF is an Augmented Dickey-Fuller (1981) test for a unit root in $\hat{\beta}_{S,t}$, The 5% critical value for the ADF test is –3.41.

Table 4: Sources of Asymmetry in $\hat{\beta}_{S,t}$

	BASIC	TOTLF	HLTH	PUBLS	RTAIL	RLEST
ϕ_1	0.994*	0.962*	0.899*	0.979*	1.132*	0.9156*
	(0.003)	(0.004)	(0.006)	(0.003)	(0.005)	(0.006)
ϕ_2	0.008	0.002	-0.042*	-0.018*	0.003	-0.011
	(0.007)	(0.009)	(0.011)	(0.006)	(0.010)	(0.012)
ϕ_3	0.055*	0.052*	0.019*	0.017*	0.055*	0.030*
	(0.007)	(0.011)	(0.008)	(0.005)	(0.009)	(0.009)
ϕ_4	-0.003	-0.009	-0.040	-0.021*	-0.005	-0.065*
	(0.007)	(0.009)	(0.011)	(0.006)	(0.011	(0.011)
ϕ_5	0.012*	-0.031	-0.021*	-0.003	-0.009	-0.035*
	(0.006)	(0.010)	(0.006)	(0.005)	(0.006)	(0.006)
ϕ_6	-0.031	-0.014	-0.014	-0.005	-0.028*	-0.015*
	(0.006)	(0.011)	(0.008)	(0.005)	(0.009)	(0.008)
ϕ_7	-0.034	-0.016	-0.005	-0.019*	-0.022*	-0.014*
	(0.007)	(0.010)	(0.006)	(0.004)	(0.006)	(0.006)
LM	136.95	134.382	98.0915	190.263	81.865	277.212
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Notes to Table 4: Marginal significance levels displayed as [.]. Standard errors displayed as (.). * denotes significance at the 5% level.

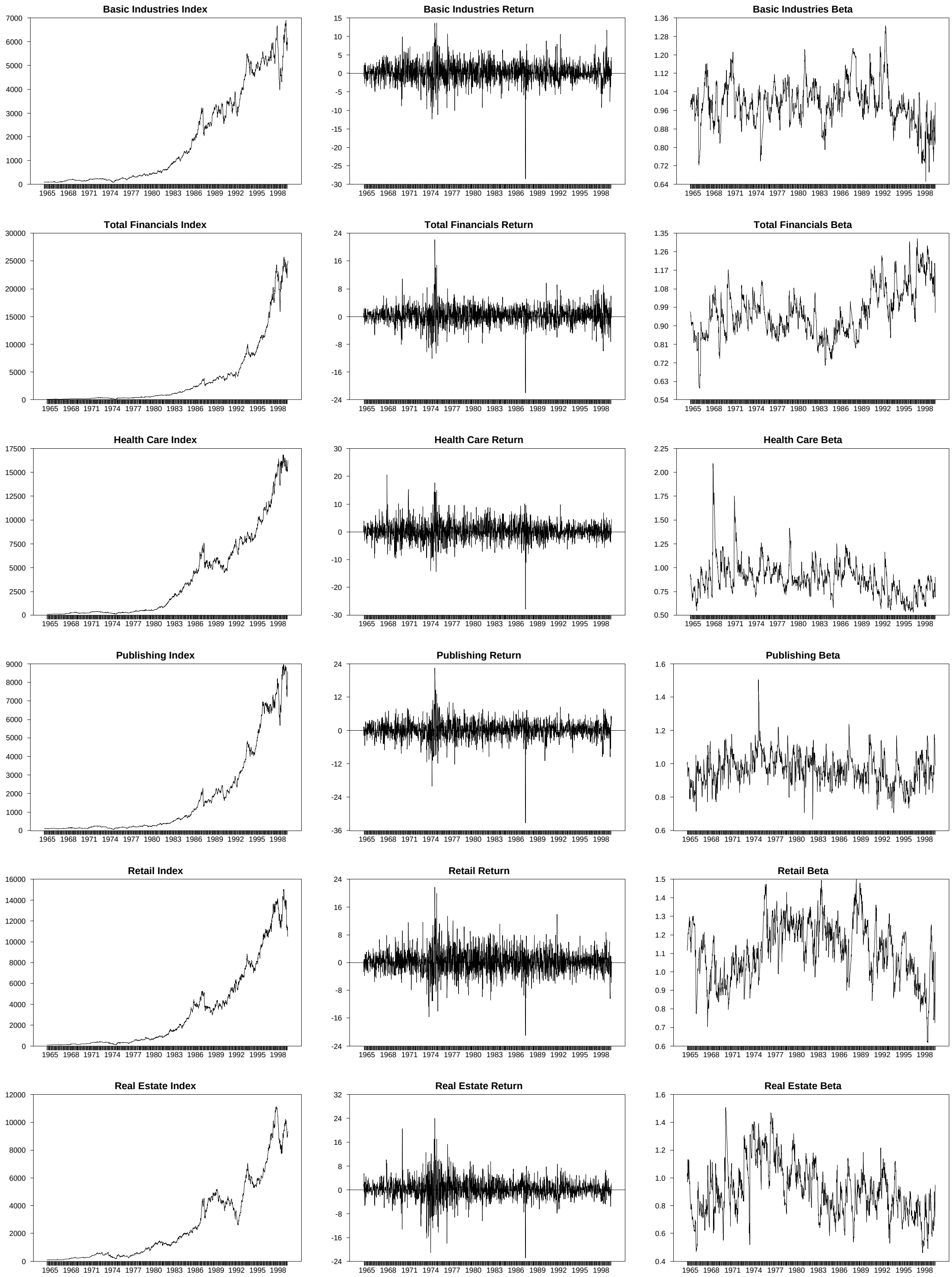

Figure 1: Sector index, sector return and estimated sector beta

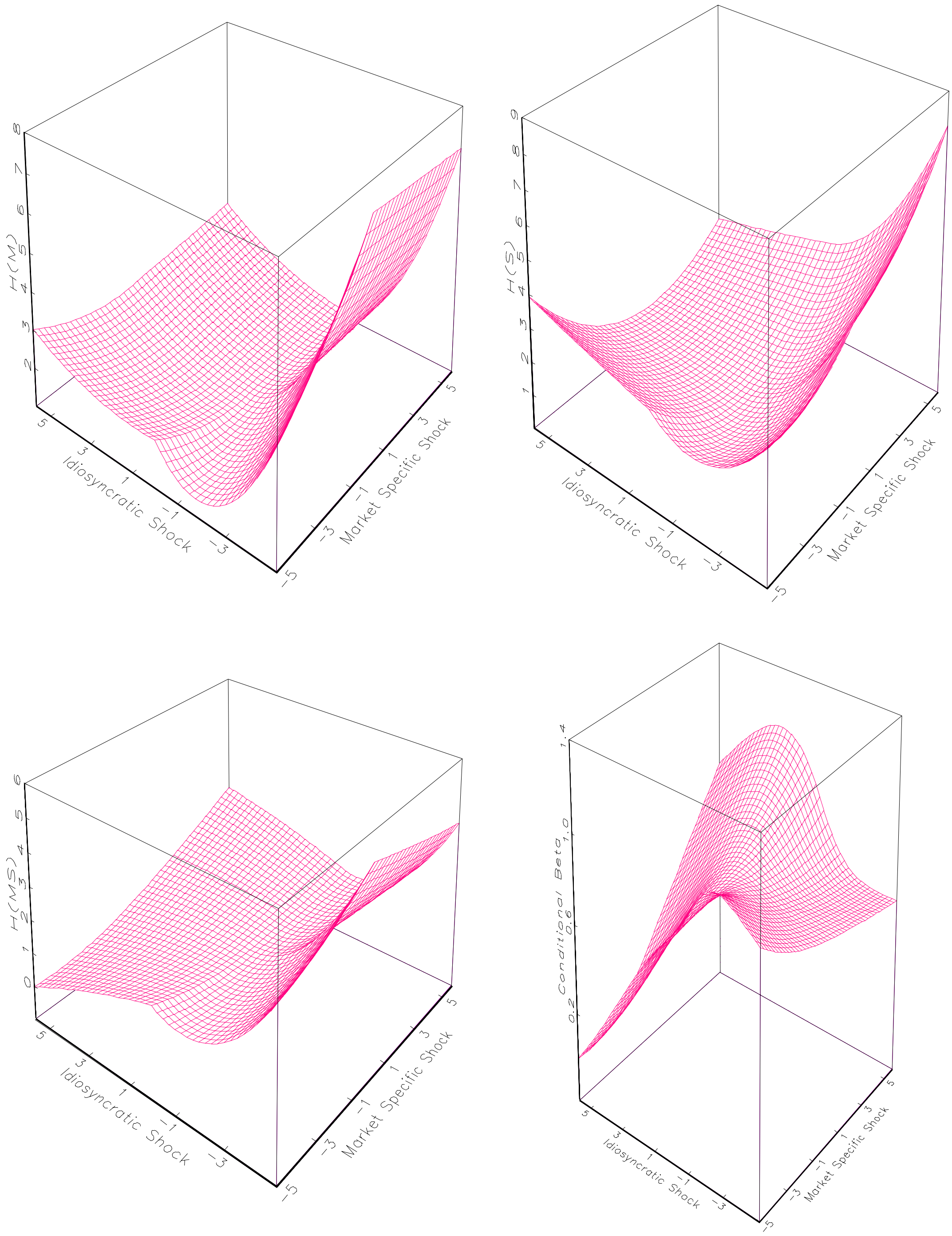

Figure 2: News Impact Surfaces for Basic Industries

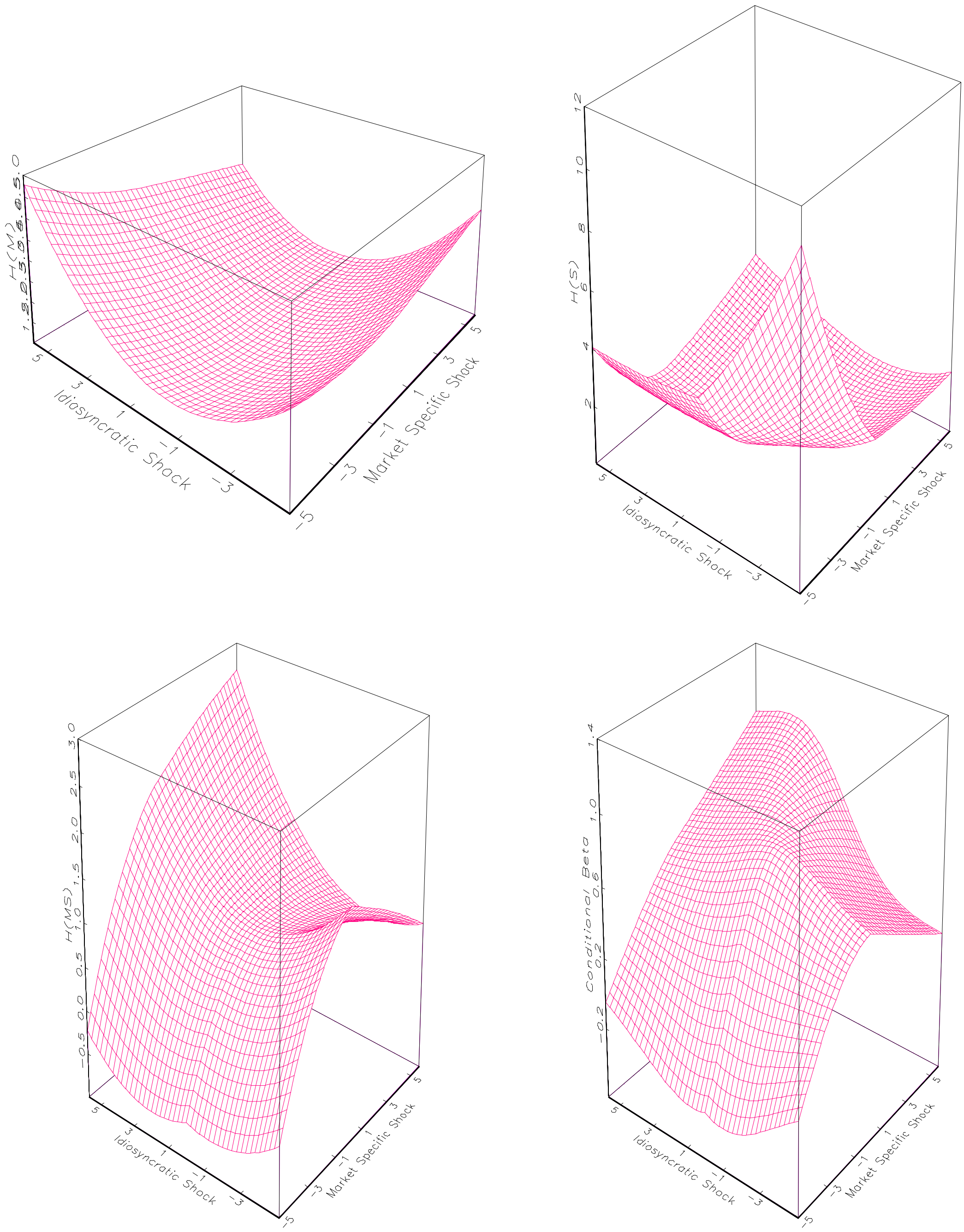

Figure 3: News Impact Surfaces for Total Financial

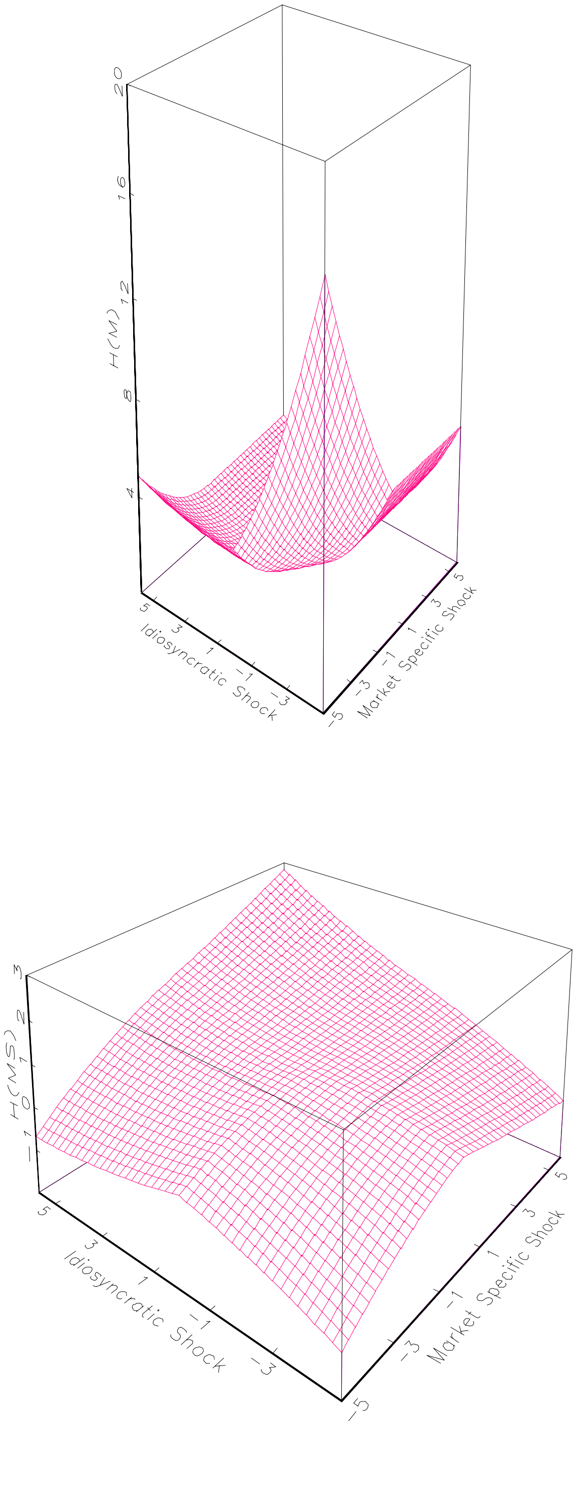

Figure 4: News Impact Surfaces for Healthcare

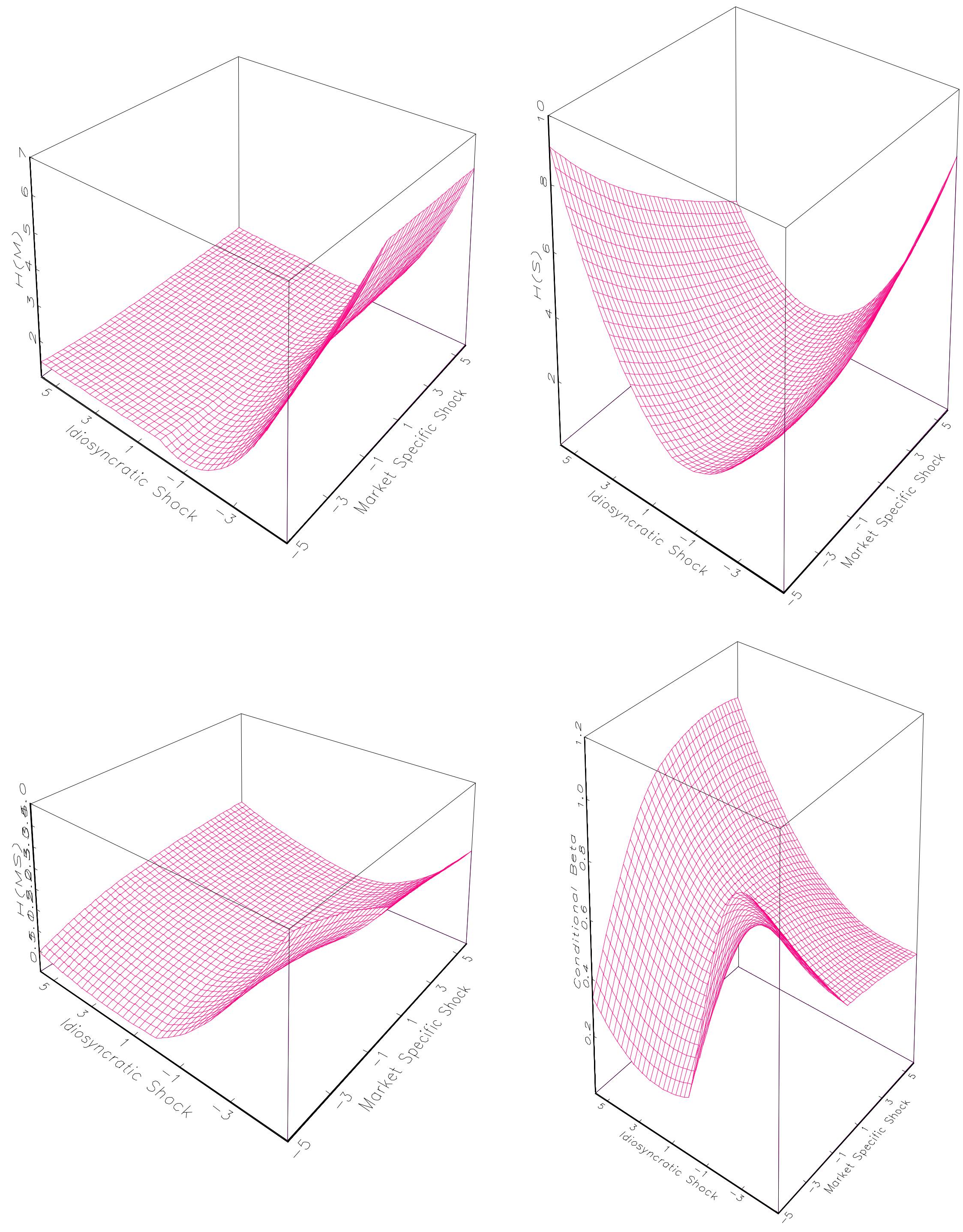

Figure 5: News Impact Surfaces for Publishing

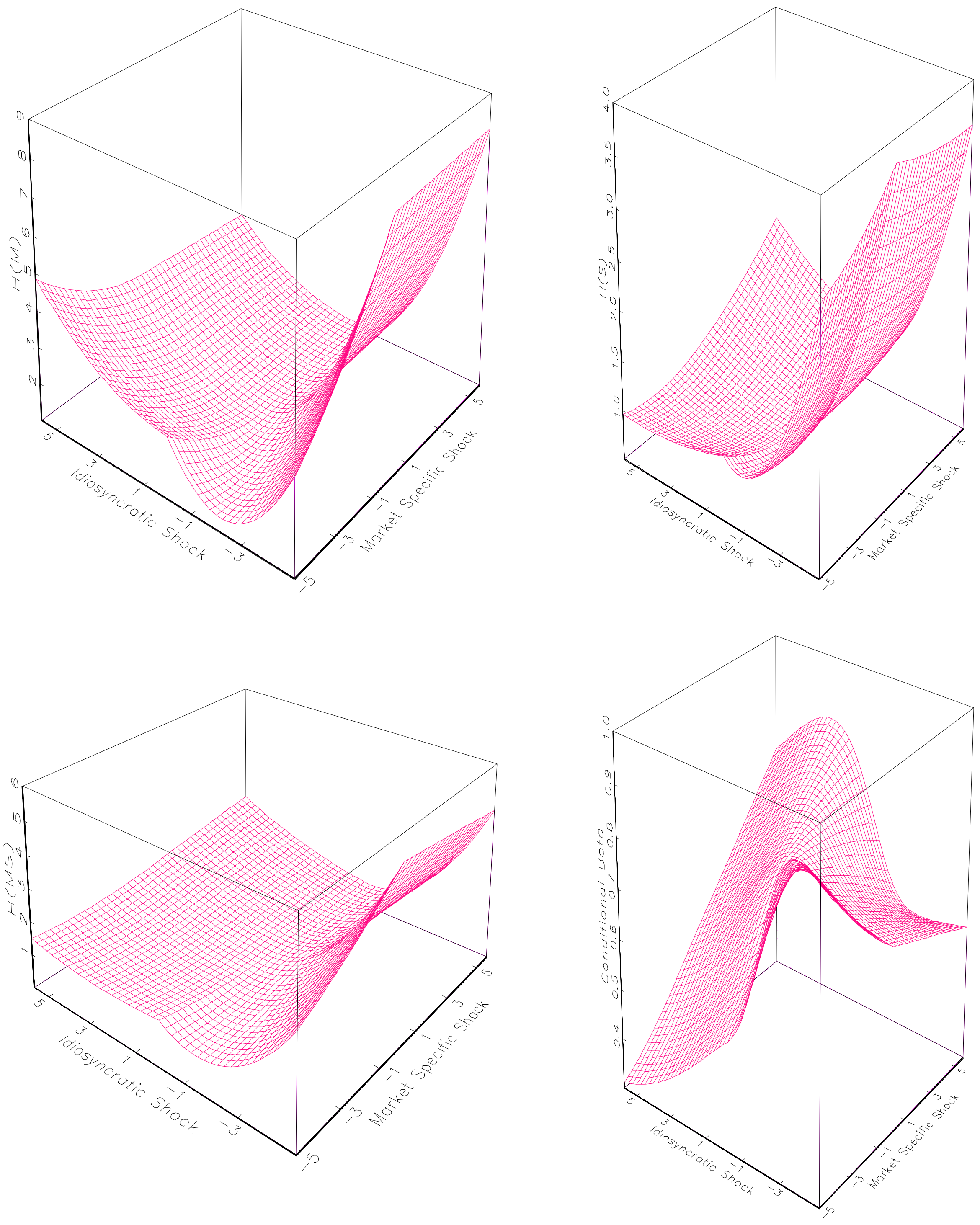

Figure 6: News Impact Surfaces for Retail

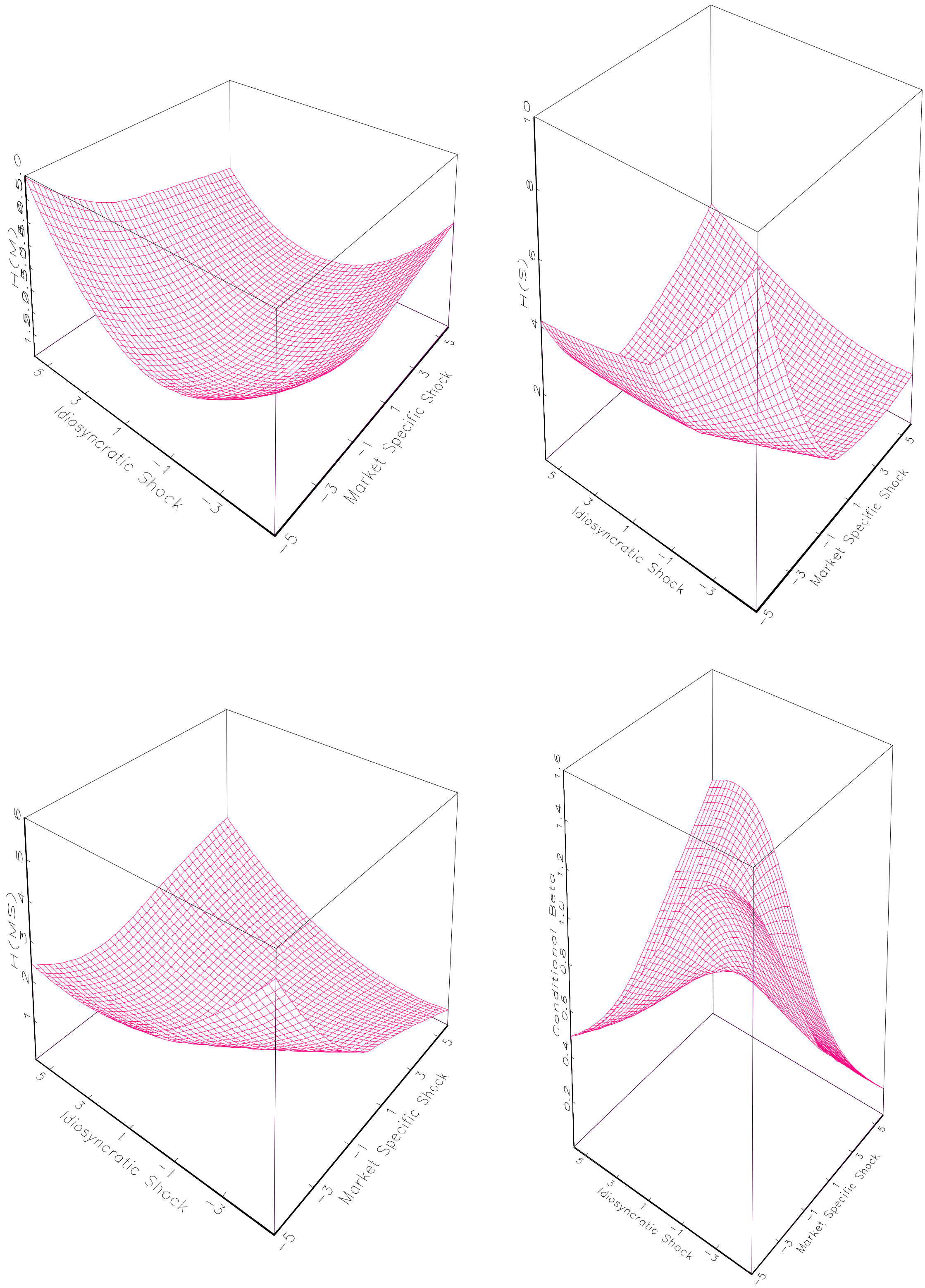

Figure 7: News Impact Surfaces for Real Estate