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ASYMMETRIC COVARIANCE, VOLATILITY, AND THE EFFECT OF NEWS

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Abstract

We propose that covariance (rather than beta) asymmetry provides a superior framework for examining issues related to changing risk premiums. Accordingly, we investigate whether the conditional covariance between stock and market returns is asymmetric in response to good and bad news. Our model of conditional covariance accommodates both the sign and magnitude of return innovations, and we find significant covariance asymmetry that can explain, at least in part, the volatility feedback of stock returns. Our findings are consistent across firm size, firm leverage, and temporal and cross-sectional aggregations.

JEL Classification: G12

I. Introduction

Investigation of the time-series properties of conditional second moments of returns is an active area of contemporary empirical finance research, particularly in the context of asset pricing. Many studies in this literature examine the time-series properties of beta, and volatility. In the current article we contribute to this literature by focusing on conditional covariance (as opposed to beta) and its asymmetric properties as a framework in which we can better meet some of the empirical challenges of asset pricing theory.

Fundamentally, we argue that any beta asymmetry is difficult to detect because shocks affect both the conditional variance and conditional covariance (the numerator and denominator) in a similar way, thereby disguising the asymmetric response to news. Our view amplifies that of Bekaert and Wu (2000), who suggest that covariance asymmetry arises more naturally than beta asymmetry. To appreciate this, assume that the beta of a firm is positive and constant over time. A rise in the market's conditional variance requires a similar proportional rise in the conditional covariance, and if the market's variance is asymmetric, the firm's covariance will

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also be asymmetric. Thus, in attempting to find asymmetry in beta, researchers are confronted with an artificial construct that may have asymmetry in both numerator and denominator, within finite time intervals. As acknowledged by Bekaert and Wu, although betas do vary over time, possibly in an asymmetric manner, there is no model that predicts such behavior at the firm level. Accordingly, we contend that modeling conditional covariance (rather than conditional beta) provides a superior framework in which to examine issues related to changing risk premiums.

We engage the challenge of explaining the observed asymmetric effect of news on stock return volatility, first reported by Black (1976), to motivate our work. Early explanations offered by Black (1976) and Christie (1982) center on the role of financial and operating leverage. Others such as Pindyck (1984) and French, Schwert, and Stambaugh (1987) suggest that the asymmetric nature of the volatility response to news is due to volatility feedback. If volatility, as a measure of risk, is priced, any news that changes the price of the stock, either positively or negatively, will result in an anticipated increase in volatility, raising the required return on equity and leading to an immediate stock price decline. Asymmetry in volatility will be observed because the stock price decline compounds bad news and moderates the price rise resulting from good news.[1]

Although most studies into the effect of news on second moments focus on the U.S. market (Campbell and Hentschel 1992; Braun, Nelson, and Sunier 1995; Cho and Engle 1999; Wu 2001), only limited work is directed toward other markets (e.g., Japan; Bekaert and Wu 2000). We analyze an Australian equity market sample to broaden the research focus and help address the concern of data snooping (Leamer 1983; Lo and MacKinlay 1990). As commonly recognized in the literature, the Australian market is much smaller than the U.S. market (in 2000: US$373 billion vs. US$15,104 billion), has considerably inferior total value traded (in 2000: US$226 billion vs. US$31,862 billion), and is typified by far fewer companies (in 2000: 1,330 vs. more than 7,000 listed stocks) of much smaller size. Moreover, the Australian market has trading that is more heavily concentrated in stocks of the largest listed companies, has regulatory restrictions (e.g., to do with short selling) that differ from the United States, and is far more heavily dominated by its mining and resource sector. (Source: *Emerging Stock Markets Factbook 2001;* see also Brailsford and Faff 1993).

We examine the effect of news on the covariance of returns between individual stocks and the market, and investigate any subsequent effect on volatility and risk premiums that may help explain volatility asymmetry. Our results confirm pervasive significant conditional covariance asymmetry in response to news shocks. Such strong evidence of covariance asymmetry helps explain asymmetric volatility

[1]Three main assumptions underlie volatility feedback: (1) a conditional capital asset pricing model (CAPM) applies, (2) volatility persists, and (3) a positive intertemporal relation exists between expected return and conditional variance (see Bekaert and Wu 2000).

at both the market and firm levels, and it supports the hypothesis that time-varying risk premiums, driven by conditional covariances, may be able to explain the mean reversion of asset prices.

Our main contributions to research in this field are threefold. First, we show that the use of conditional beta in estimating time-varying risk premiums can be inconclusive and propose that conditional covariance is a superior instrument for examining such issues. Second, we find robust evidence of covariance asymmetry that helps explain volatility feedback at the individual firm level that is independent of firm size or firm leverage. Finally, we propose a model of conditional covariance that allows for full asymmetry (i.e., sign and magnitude effects), is robust to temporal and cross-sectional aggregation, and can be used on any number of stocks.

II. Possible Effects of Asymmetric Conditional Covariance

Covariance and Volatility Feedback

Bekaert and Wu (2000) investigate both the leverage effect and volatility feedback explanations of asymmetric volatility. Using a multivariate generalized autoregressive conditional heteroskedsticity (GARCH) model on leverage portfolios, they reject the pure leverage effect of Christie (1982) and suggest the main mechanism behind volatility asymmetry is volatility feedback. In particular, they find that volatility feedback is strongest when conditional covariances respond asymmetrically to market shocks, that is, when negative shocks have a greater effect on conditional covariance than positive shocks.

To illustrate the role of covariance in volatility feedback and therefore asymmetric volatility, assume that a conditional version of the CAPM holds (Merton 1980):

$$E[r_{i,t} \mid \Psi_{t-1}] = \lambda_t \text{cov}(r_{i,t}, r_{m,t} \mid \Psi_{t-1}) \, \forall \, i \tag{1}$$

and

$$\lambda_t = \frac{E[r_{m,t} \mid \Psi_{t-1}]}{E[\text{var}(r_{m,t}) \mid \Psi_{t-1}]}, \tag{2}$$

where λ_t is the market price of risk at time *t,* and $r_{i,t}$ and $r_{m,t}$ are the excess returns on an asset *i* and the market at time *t*.

Consider the effect of a general market-level shock, say, the release of bad news that affects the whole market. From Figure I (adapted from Bekaert and Wu 2000), we see that the release of news will increase the current volatility of returns in the market, which will increase, ceteris paribus, the covariance between asset returns and market returns (remember $\text{cov}(r_i, r_m) = \rho_{im,t}\sigma_{i,t}\sigma_{m,t}$ by definition). Because

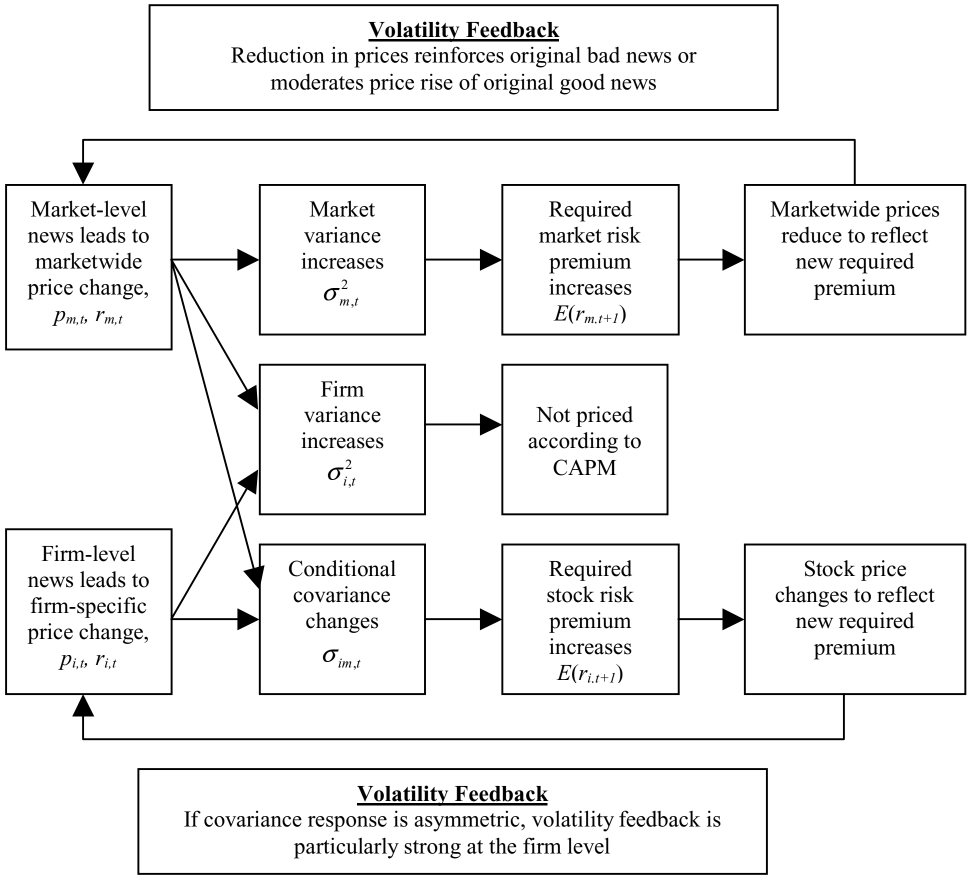

Figure I. Flow of News Effect at Market and Firm Levels.

conditional covariance is persistent (see Bekaert and Wu 2000), investors will revise upward estimates of future conditional covariance, which will increase the required risk premium on all assets. This sequence of effects will lead to an immediate decline in the current value of the market. The price decline will continue until the expected return is sufficiently high in equilibrium. As is the case in volatility feedback, this covariance feedback will reinforce the initial price drop and create further volatility in the market. Second, the marketwide price decline leads to higher leverage at the market level, and this will increase the required risk premium across the market and create higher covariance, again reinforcing the price drop and creating further volatility in the market.

When good news arrives in the market, there are again two effects. First, the news brings about higher current-period volatility and covariance with the change in price, and investors will again revise upward their estimates of next period's covariance. Prices will decline to induce higher expected returns, dampening the initial price movement. Second, the marketwide price increase reduces leverage and therefore the required market risk premium. Overall, the effect on stock return volatility is not clear.

Referring to Figure I, we can see the effect of firm-specific shocks and the mechanism by which volatility feedback can lead to asymmetric volatility at the firm level. Under the CAPM, a firm is priced according to its contribution to market risk in a well-diversified portfolio, not its own idiosyncratic risk or variance. News at the firm level can only create asymmetric volatility through a change in leverage because idiosyncratic variance is not priced. However, if we can establish a link between firm-specific shocks and risk premiums, through conditional covariance, the effect of volatility asymmetry should be stronger at the firm level, more so if we can show that the conditional covariance is asymmetric. Bekaert and Wu (2000) find evidence of covariance asymmetry in leverage portfolios constructed from Nikkei 225 stocks.

Covariance and Mean Reversion

Braun, Nelson, and Sunier (1995) use a bivariate exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model with monthly portfolio returns to investigate the market risk premium using conditional betas. Although they find strong evidence of asymmetric market volatility, they find no evidence of asymmetric response in conditional betas and, hence, conclude that time variation in beta is not responsive enough to account for the mean reversion in stock prices.

Employing a similar model to Braun, Nelson, and Sunier (1995), but using daily, individual stock data, Cho and Engle (1999) report an asymmetric effect of news on the beta of individual stocks. Cho and Engle suggest that stock price aggregation and the use of monthly data by Braun, Nelson, and Sunier significantly reduce the ability of the Braun, Nelson, and Sunier tests to detect asymmetric effects. However, the Cho and Engle results are not consistent across their small sample and they report some low, even negative, autoregressive coefficients in volatility for most stocks. Nevertheless, the finding of significant asymmetry in beta at the firm level is encouraging and provides some support for the hypothesis of Chan (1988) and Ball and Kothari (1989) that time-varying betas and expected risk premiums might explain the mean reversion in asset prices.

It is our hypothesis that asymmetry in beta risk is difficult to detect because of the interaction between conditional covariance and conditional volatility in the definition of a conditional beta, particularly when both series exhibit asymmetry. Bekaert and Wu (2000) suggest that stock return betas are less likely to show leverage effects than covariances, which may provide some reasoning for Braun, Nelson, and Sunier's (1995) finding of no significant asymmetric effects in beta.

Because betas are simply scaled covariances of returns with sources of risk, examining covariances for evidence of the asymmetric effects of news is a more natural way to examine whether the systematic risk of an asset varies asymmetrically. We submit that the well-established asymmetric volatility of stock returns (e.g., see Nelson 1991; Glosten, Jagannathan, and Runkle 1993) as the denominator in the beta construct confounds empirical estimation of the beta relation. As such, focusing on beta makes it difficult for researchers to discern the real relation that exists between market and idiosyncratic shocks and systematic, or undiversifiable risk.

Accordingly, we argue that when looking for evidence of the asymmetric effect of news on expected returns, and therefore conditional volatility, whether individually or across a portfolio of stocks, it is asymmetry of covariance that is important. We propose that time-varying covariances are a simpler and more natural way to examine both asymmetric volatility and mean reversion of stock prices, leading to a clearer understanding and interpretation of the effects of news on conditional second moments.

III. Empirical Framework

Econometric Model

Following Merton (1980), we can model the returns process for the market and asset i as:[2]

$$\begin{aligned} r_{m,t} &= \sigma_{m,t} z_{m,t}, \\ r_{i,t} &= \lambda_t \sigma_{im,t} + \sigma_{i,t} z_{i,t}, \end{aligned} \tag{3}$$

where $z_{m,t}$ and $z_{i,t}$ are uncorrelated independent and identically distributed (i.i.d.) processes with zero mean and unit variance, $\sigma_{m,t}$ and $\sigma_{i,t}$ represent the conditional variance process, and $\sigma_{im,t}$ is the conditional covariance between the return on asset i and the market return.

Given the asymmetry noted in the market variance, we specify a univariate EGARCH process for the market returns (see Nelson 1992):

$$\ln\left(\sigma_{m,t}^2\right) = \alpha_m + \delta_m\left[\ln\left(\sigma_{m,t-1}^2\right) - \alpha_m\right] + \theta_m z_{m,t-1} + \gamma_m[|z_{m,t-1}| - E|z_m|]. \tag{4}$$

The EGARCH model accounts for asymmetry through the parameter θ_m. Taken together, the terms $\theta_m z_{m,t-1}$ and $\gamma_m[|z_{m,t-1}| - E|z_m|]$ allow the market conditional variance to respond asymmetrically to positive and negative returns.

[2]To eliminate residual serial correlation, the reported market model estimation included a constant term, an autoregressive term, and a day-of-the-week dummy variable. The results are robust to this variation.

We employ a method of estimating time-varying conditional covariances based on the EGARCH model of Nelson (1991), allowing for the possibility that positive and negative return shocks affect covariances differently:

$$\sigma_{im,t} = \alpha_{ci} + \delta_{ci}[\sigma_{im,t-1} - \alpha_{ci}] + \Phi(z_{m,t-1}) + \Phi(z_{i,t-1}) + \theta_{cim} z_{m,t-1} z_{i,t-1}, \quad (5)$$

$$\Phi(z_{k,t-1}) = \theta_{ck} z_{k,t-1} + \gamma_{ck}[|z_{k,t-1}| - E|z_k|],\ k = i,m, \quad (6)$$

where the news response function, $\Phi(z_{k,t-1})$, allows for a full asymmetric response to return innovations.[3] That is, conditional covariance can respond to both the sign and the magnitude of both market and firm shocks. The parameter θ_{cm} in $\Phi(z_{m,t-1})$ (θ_{ci} in $\Phi(z_{i,t-1})$) measures the response of the conditional covariance to the sign of the market (firm) shock, and γ_{cm} (γ_{ci}) measures the response to the magnitude of the market (firm) shock. If $-1 < \theta_{cm} < 0$ with γ_{cm} positive, conditional covariance increases more in response to negative innovations than to positive innovations of the same magnitude. The same applies for firm-specific shocks. The main difference between our specification and that of Braun, Nelson, and Sunier (1995) and Cho and Engle (1999) is that we allow for a full asymmetric response to the news events. Specifically, the previous authors do not allow for magnitude effects in their specification.

The cross term θ_{cim} in (5) represents a cross-product, or joint asymmetry, effect in conditional covariance. Specifically, if θ_{cim} is positive, the conditional covariance rises when the market and idiosyncratic returns move in the same direction (either both positive or both negative) and falls when the two returns move in opposite directions.

Modeling the conditional covariance this way allows us to examine directly the effect of news on the conditional expected returns. Any asymmetric effects, at either the market or firm level, will manifest themselves through the coefficients of the standardized return innovations. Significance of the theta and gamma coefficients allows us to examine the arguments of Chan (1988) and Ball and Kothari (1989) for time-varying expected premiums. Also, it is possible for the model to generate volatility asymmetry in response to market shocks without generating covariance asymmetry or to generate simultaneously reverse covariance asymmetry.

Finally, we specify the return volatility of asset i as an EGARCH process:

$$\ln\left(\sigma_{i,t}^2\right) = \alpha_i + \delta_i\left[\ln\left(\sigma_{i,t-1}^2\right) - \alpha_i\right] + \theta_i z_{i,t-1} + \gamma_i[|z_{i,t-1}| - E|z_i|]. \quad (7)$$

Although we already explicitly allow for asymmetric effects in the modeling of covariance, we again use this specification in case there are residual asymmetry effects that cannot be completely captured by the covariance specification. As before,

[3]To denote clearly that all coefficients in this model belong to a covariance specification, we employ a leading c subscript for each coefficient.

asymmetric effects of the asset-specific variance occur through the operation of $\theta_i z_{i,t-1}$ and $\gamma_i[|z_{i,t-1}| - E|z_i|]$.

Finally, referring to equation (3), we need to estimate a conditional market price of risk, λ_t. The coefficient λ_t is a scalar related to the aggregate relative risk aversion of the economy (Merton 1980), and we form an estimate by assuming that the realized excess market returns are an unbiased estimate of investors' conditional expected excess returns, and we divide this by the estimated conditional market variance (refer to equation (2)).

The complete model therefore allows the conditional second moments of both the individual asset returns and the market returns to respond asymmetrically to the arrival of news, at both the market level and the firm level. Because we formulate firm returns in terms of conditional covariance with the market, all that is required to demonstrate volatility feedback is a dependence of covariance and firm volatility on market shocks.

Estimation Procedure

We estimate the model by first demeaning both the market and individual excess returns and fitting an EGARCH(1,1) model to estimate the conditional market variance.[4] Then, for each stock, conditional covariance and conditional variance equations are simultaneously estimated using market volatility as a fixed input for the estimation of the conditional price of risk. We find that this method is parsimonious and efficient, with the advantage that the market residuals and conditional variance are consistent across the sample. For each univariate estimation we assume the generalized error distribution (GED) (Nelson 1991) and maximize the log likelihood using the BHHH algorithm (Berndt et al. 1974).

Data Description

The data, from Datastream International, are daily total returns from January 5, 1988, to November 25, 1999. To keep things manageable, we sample 50 stocks from the Australian Stock Exchange (ASX) universe (totaling approximately 1,300), of which we select 20 stocks from the top 50 according to market capitalization (measured just before the start of our sample period), and the remaining 30 stocks are randomly chosen from outside the top 50. To conserve space, we focus on the 20 stocks sampled from the top 50.[5] In terms of market capitalization

[4]The use of demeaned returns follows Braun, Nelson, and Sunier (1995) and Cho and Engle (1999) as it simplifies estimation and does not affect parameter estimates when estimating conditional second moments (Nelson 1992).

[5]There is strong internal consistency of our findings, suggesting that our samples of 20 and 50 are both broadly representative of the population. Our sample does contain some small cap stocks; indeed, the smallest inclusion has a market capitalization of AUD$220,000, comfortably placing it in the smallest decile of ASX stocks.

(as measured at the end of 1987) our subsample of 20 has an aggregate capitalization of AUD$65 billion, which represents approximately one-third of the total ASX equity capitalization at that time. The proxy for the risk-free rate is the 90-day bank bills total return index. For each series there are 3,103 usable observations in our sample, and as expected, all series are skewed and leptokurtotic. Most series exhibit serial correlation and all series show heteroskedasticity.

IV. Estimation Results

Diagnostic Checking

Although we suppress detailed results of all diagnostic checking to conserve space, the current subsection provides a broad overview of their encouraging nature. Selection of an appropriate EGARCH model is essentially an empirical question based on both formal and heuristic examination of the standardized residuals. Mean, variance, and symmetry (orthogonality) tests (Nelson 1991) are performed, and the residuals from all stocks pass these tests. We also test for residual autocorrelation and heteroskedasticity in the standardized residuals, via Ljung-Box Q and Q^2 tests up to lag 24. Although there appears to be some residual autocorrelation and heteroskedasticity in the standardized residuals, it is unrealistic when using daily returns to expect any empirical model to account completely for the higher moments in the estimation. Additionally, our main focus is on conditional second moments, and Nelson (1992) shows that misspecification in the conditional means does not affect the key properties of the second moments. Finally, we also perform sign bias, negative size bias, and positive size bias tests, and joint tests on both series of residuals (Engle and Ng 1993). Overall, the model appears well specified with only a few stocks failing individual tests, but no stock fails more than one test at a time. Taking into account all diagnostic tests, the model is sufficiently well specified.

Market Variance

Table 1 contains the parameter estimates for the demeaned excess market returns specified as following a univariate EGARCH(1,1) model. As to be expected using daily data, there is strong persistence evident in the market's conditional variance with the lagged volatility coefficient, δ_m, estimate of 0.93. We find evidence of significant asymmetric volatility of market returns with $\theta_m = -0.0565$ and $\gamma_m = 0.1625$. That is, conditional market volatility rises more with negative market return shocks and unexpected large shocks than with positive market return shocks and expected return shocks. Finally, the estimated GED coefficient is 1.36, indicating that the nature of the distribution of the demeaned market return is leptokurtic, as expected with daily returns.

TABLE 1. Estimation of the EGARCH Model on the Market Return.

Panel A. Estimation Results

	Coefficient	t-statistic	p-value
ω_m	−0.0029	−0.181	0.8559
β_m	0.0894	5.217	0.0000
α_m	−0.1457	−11.156	0.0000
δ_m	0.9316	96.816	0.0000
γ_m	0.1625	11.112	0.0000
θ_m	−0.0565	−6.039	0.0008
GED(ν)	1.3581	39.298	0.0000

Panel B. Diagnostic Test of Market Standardized Residuals

Test	t-statistic	p-value
$z_m = 0$	−0.093	0.926
$\mathrm{var}(z_m) = 1$	0.010	0.992
$z_m\|z_m\| = 0$	−1.060	0.289
$Q(z_m)_{24}$	29.013	0.220
$Q({z_m}^2)_{24}$	16.126	0.883

Note: This table reports univariate exponential generalized autoregressive conditional heteroskedasticity (EGARCH) estimation using daily stock return data for equally weighted market return from January 5, 1988, to November 25, 1999. Parameters are estimated by maximum likelihood using the following specification:

$$r_{m,t} = \omega_m + \beta_m \cdot r_{m,t-1} + \sigma_{m,t} z_{m,t}, \tag{3'}$$

$$\ln\left(\sigma^2_{m,t}\right) = \alpha_m + \delta_m\left[\ln\left(\sigma^2_{m,t-1}\right) - \alpha_m\right] + \theta_m z_{m,t-1} + \gamma_m[|z_{m,t-1}| - E|z_m|], \tag{4}$$

where $\ln(\sigma^2_{m,t})$ is the log of the conditional variance of the market return, $z_{m,t}$ is the standardized residual for the market portfolio and is calculated as $z_{m,t} = r_{m,t}/\sigma_{m,t}$ where $r_{m,t}$ is the demeaned excess return on the market portfolio. Equation (3) is estimated to include a day-of-the-week dummy variable (for Tuesday) and because its coefficient is insignificant it is unreported. Error terms are assumed to follow the generalized error distribution (GED) of Nelson (1991).

Covariance

Table 2 displays the outcome of estimating the conditional covariance equations for a representative subsample of 20 stocks.[6] We can see that conditional covariance is persistent with δ_{ci}, the autoregressive term, across the 20-stock sample averaging 0.932, with a high of 0.962. Reported t-statistics (noted in parentheses) are all high. The GED parameter (unreported) averages 1.20 across the sample,

[6]To conserve space, we suppress details of the other equation parameter estimates for the 20 stocks. Moreover, the results across the full sample are strongly robust and the reported cases are truly representative. Full details are available from the authors on request.

TABLE 2. Covariance Equation Estimation Results, Daily Individual Stock Data.

Stock	α_{ci}	δ_{ci}	θ_{ci}	γ_{ci}	θ_{cm}	γ_{cm}	θ_{cim}
AMCO	0.2270**	0.9380**	0.0230**	−0.2885**	0.0012	−0.0658**	−0.0116**
	(31.57)	(253.63)	(6.62)	(−41.28)	(0.20)	(−7.97)	(−5.00)
ANBG	0.0757**	0.9192**	−0.0200**	0.0451**	−0.0535**	0.1108**	0.0218**
	(9.90)	(110.49)	(−3.27)	(4.53)	(−8.26)	(10.11)	(3.72)
BHPY	0.0582**	0.9401**	0.0031	0.0176**	−0.0396**	0.1185**	0.0164**
	(13.90)	(204.10)	(1.04)	(3.41)	(−10.85)	(18.85)	(5.13)
BORA	0.0613**	0.9253**	0.0050	0.0050	−0.0335**	0.1195**	0.0256**
	(7.72)	(91.01)	(0.80)	(0.49)	(−5.17)	(10.31)	(4.04)
BRAI	0.0398**	0.9409**	0.0054	0.0011	−0.0405**	0.0800**	0.0076
	(7.52)	(121.53)	(1.06)	(0.14)	(−7.64)	(8.66)	(1.72)
COLE	0.0544**	0.9239**	−0.0044	0.0384**	−0.0323**	0.0983**	0.0225**
	(9.10)	(105.24)	(−0.83)	(4.71)	(−5.85)	(10.17)	(4.47)
CRAM	0.0542**	0.9418**	−0.0018	−0.0093	−0.0388**	0.1208**	0.0205**
	(9.91)	(152.31)	(−0.40)	(−1.23)	(−7.77)	(12.93)	(5.27)
CSRA	0.0290**	0.9620**	−0.0118**	0.0044	−0.0365**	0.0725**	0.0044
	(8.56)	(207.07)	(−2.95)	(0.72)	(−8.81)	(10.19)	(1.31)
FOST	0.0535**	0.9357**	−0.0124	0.0449**	−0.0647**	0.1033**	0.0377**
	(9.29)	(129.41)	(−1.62)	(4.49)	(−8.64)	(8.98)	(5.71)
GPTS	0.0443**	0.8882**	0.0059	0.0011	−0.0207**	0.0733**	0.0265**
	(5.25)	(40.79)	(0.80)	(0.11)	(−3.08)	(6.21)	(4.08)
ICIA	0.0572**	0.8923**	0.0198**	0.0058	−0.0454**	0.0871**	0.0406**
	(5.92)	(50.08)	(2.24)	(0.49)	(−5.54)	(6.71)	(4.71)
LEND	0.0437**	0.9244**	−0.0052	−0.0038	−0.0244**	0.0817**	0.0255**
	(6.93)	(81.81)	(−0.97)	(−0.55)	(−4.30)	(8.45)	(5.04)
MIMA	0.0452**	0.9589**	−0.0017	−0.0144	−0.0480**	0.1316**	0.0369**
	(7.34)	(167.83)	(−0.23)	(−1.24)	(−6.47)	(9.54)	(5.10)
NABK	0.2064**	0.9197**	0.0289**	−0.2393**	−0.0253**	−0.0763**	−0.0236**
	(10.00)	(714.78)	(9.80)	(−47.46)	(−4.48)	(−14.46)	(−15.67)
NECO	0.0673**	0.9329**	0.0051	0.0386**	−0.0428**	0.1146**	0.0497**
	(8.89)	(124.25)	(0.77)	(3.23)	(−5.84)	(9.97)	(6.67)

(Continued)

TABLE 2. Continued.

Stock	α_{ci}	δ_{ci}	θ_{ci}	γ_{ci}	θ_{cm}	γ_{cm}	θ_{cim}
PACD	0.0520**	0.9380**	0.0060	0.0122	−0.0386**	0.1252**	0.0165**
	(9.80)	(143.49)	(1.03)	(1.56)	(−7.35)	(12.60)	(3.16)
SANT	0.0396**	0.9318**	−0.0036	−0.0136	−0.0425**	0.0782**	0.0305**
	(5.47)	(76.10)	(−0.50)	(−1.26)	(−5.86)	(6.86)	(4.09)
WEBA	0.0701**	0.9203**	0.0039	0.0318**	−0.0332**	0.1138**	0.0171**
	(9.52)	(106.28)	(0.73)	(3.68)	(−5.90)	(11.63)	(3.24)
WMCX	0.0469**	0.9525**	−0.0053	−0.0004	−0.0391**	0.1201**	0.0356**
	(7.55)	(147.00)	(−0.87)	(−0.04)	(−5.89)	(10.10)	(5.50)
WOOD	0.0273**	0.9507**	0.0113	0.0013	−0.0169**	0.0469**	0.0412**
	(4.36)	(90.28)	(1.65)	(0.12)	(−2.53)	(4.38)	(5.46)
Average	0.0677	0.9318	0.0026	−0.0161	−0.0358	0.0827	0.0221
p-value	(0.0000)	(0.0000)	(0.3382)	(0.4088)	(0.0000)	(0.0000)	(0.0000)
p-value	[0.0000]	[0.0000]	[0.8231]	[0.2636]	[0.0001]	[0.0008]	[0.0008]

Note: This table shows simultaneous estimates using daily stock return data for the period January 5, 1988, to November 25, 1999. Parameters are estimated by maximum likelihood using the system of equations (5), (6) and (7) in the text. The covariance specification is given by:

$$\sigma_{im,t} = \alpha_{ci} + \delta_{ci}[\sigma_{im,t-1} - \alpha_{ci}] + \Phi(z_{m,t-1}) + \Phi(z_{i,t-1}) + \theta_{cim} z_{m,t-1} z_{i,t-1}, \tag{5}$$

where

$$\Phi(z_{k,t-1}) = \theta_{ck} z_{k,t-1} + \gamma_{ck}[|z_{k,t-1}| - E|z_k|],\ k = i,m, \tag{6}$$

where $\sigma_{im,t}$ is the estimated conditional covariance, $z_{m,t}$ is the standardized residual for the market portfolio, $z_{i,t}$ is the standardized residual for the stock. Error terms are assumed to follow the generalized error distribution (GED) of Nelson (1991). AMCO = Amcor; ANBG = ANZ Banking Group; BHPY = Broken Hill Proprietary Ltd; BORA = Boral Industries; BRAI = Brambles Industries; COLE = Coles Myer Ltd; CRAM = Rio Tinto; CSRA = CSR Ltd; FOST = Fosters Brewing Group; GPTS = General Property Trust; ICIA = Orica; LEND = Lend Lease Corporation; MIMA = Mount Isa Mines Ltd; NABK = National Australia Bank Ltd; NECO = News Corporation; PACD = Pacific Dunlop; SANT = Santos Mining; WEBA = Westpac Banking Group; WMCX = Western Mining Corporation; WOOD = Woodside Petroleum. In relation to individual parameter estimates, the *t*-statistic is provided in parentheses below the estimated value. In relation to overall averages, the *p*-value for the cross-sectional *t*-test (nonparametric sign test) for the hypothesis that the average parameter estimate is equal to zero is provided in parentheses (square brackets) below the reported average.

** Significant at the 5% level.

indicating the daily returns are leptokurtic and justifying the use of a specification that does not assume normality.

The parameters of primary interest for evidence of news asymmetry are θ_{cm}, γ_{cm}, θ_{ci}, γ_{ci}, and θ_{cim}. There is strong evidence of an asymmetric covariance response to news across the whole sample. This is a strong result as market- or firm-specific leverage does not appear in our estimating model; therefore, evidence of covariance asymmetry does not appear to depend on financial or operating leverage.

First, looking at the relation between market shocks and covariance (θ_{cm} and γ_{cm}) we see that the asymmetry term, θ_{cm}, is negative for every stock (except AMCO) and statistically significant for all firms. Additionally, γ_{cm} is positive in all but two cases and significant for all stocks. This is strong evidence that news at the market level has an important asymmetric effect on conditional covariance. Conditional covariance increases to a greater extent with negative market shocks and decreases to a lesser extent with positive market shocks across the whole sample. This is a powerful result and supports our hypothesis that news asymmetry at the firm level is easier to detect with covariance.

Second, in contrast to the immediately preceding results, there is little evidence that conditional covariance is affected by purely idiosyncratic (company-based) shocks. The relevant parameter estimates (θ_{ci} and γ_{ci}) do not show any consistent result, or significance, across the data set. For the 20-stock sample the asymmetry parameter, θ_{ci}, averages 0.0026 (cross-sectionally insignificant) and is individually significant for only 5 of the 20 stocks. Similarly, γ_{ci} averages -0.0161 and is significant for 8 of the 20 stocks—an improvement, but still less that half of the stocks are individually significant and the cross-sectional average is insignificant. The difference in the magnitudes of the averages is large, with the market asymmetry factor (θ_{cm}) an order of magnitude greater than its idiosyncratic counterpart (θ_{ci}). Thus, it appears that news at the firm level is not important in the conditional covariance relation, at least not by itself.

The cross term, θ_{cim}, shows a significant and positive relation with covariance in 16 of the 20 stocks. Recall that the parameter θ_{cim} represents the combined effect on covariance of both market- and firm-level shocks, of any sign. Thus, it appears that shocks to the return process at the firm level affect covariance only when there is a corresponding shock to the market return, of any sign. This is intuitively appealing because purely idiosyncratic shocks should not be priced by the market, but only when idiosyncratic news is accompanied by market-level news should investors change their expectations and equilibrium prices. The fact that joint shocks are priced, but purely firm-level shocks are not, is evidence of an efficient market.

If simultaneous shocks to the market and firm occur and are of the same sign (i.e., the shocks are both good or both bad), the effect on conditional covariance is at its largest and is positive. In particular, if both shocks are negative, we will see the largest increase in covariance. Not only will the cross-product parameter θ_{cim} add to the covariance, but (given our estimation results of a negative sign for θ_{cm})

the asymmetric function of z_m will also work similarly. The required return for the stock will move much higher, and to obtain equilibrium the relative stock price will fall considerably.

Conversely, if the market- and firm-level news are of opposite sign, the effect on conditional covariance is negative, reducing the required return and increasing the relative stock price. Thus, good news at the market level will moderate the effect of bad news at the firm level, and good news at the firm level will moderate the effect of bad news at the market level. This seems plausible and intuitively reasonable.

Taken together, these results indicate that market-level news is important and priced by investors. Furthermore, firm-level news, by itself, is not important and is not priced by investors except when there is also market-level news—when the joint effect of both shocks is the most significant parameter affecting conditional covariance.[7]

V. Discussion

Economic Significance of Covariance Asymmetry

To assess the economic significance of covariance asymmetry and volatility implied by the parameter estimates, we can look at the effect of a standard return innovation on a representative stock. By averaging the parameter estimates we can obtain a useful idea of the effect of covariance asymmetry on the expected risk premium, volatility, and beta.

As a starting point, we substitute the unconditional estimate of the market price of risk,

$$\left[\hat{\lambda} = \frac{1}{n}\sum_{t=1}^{n}\hat{\lambda}_t = \frac{1}{n}\sum_{t=1}^{n}\frac{r_{m,t}}{\hat{\sigma}^2_{m,t}} = 0.000473\right],$$

into equation (1) to obtain an estimated risk premium for the average stock. The average conditional covariance multiplied by the unconditional price of risk, λ,

[7]A brief commentary on the (unreported) variance equation results is worthwhile at this point. Generally, there is little evidence of volatility asymmetry at the firm level but consistent and significant evidence of increased volatility with larger than expected return shocks of any sign. This is evidence against the leverage hypothesis and directly supports the volatility feedback hypothesis because good news and bad news at the firm level in excess of the expected value increases conditional volatility. The absence of asymmetry is explained by remembering that conditional volatility and conditional covariance are simultaneously estimated. Our hypothesis is that the asymmetric market volatility observed is best explained and evidenced using covariance asymmetry and not firm-specific volatility. This is supported by the results of our simultaneous estimation. The covariance asymmetry that is so strongly evidenced in our results is driving the market volatility and is creating the asymmetric response to news through the effect of changing covariances on expected returns. We discuss this further in section V.

TABLE 3. Economic Effect of News.

	Effect of Market News		Joint Effect of Market and Individual Firm News			
			Firm Good News		Firm Bad News	
	Good News	Bad News	Market Good News	Market Bad News	Market Good News	Market Bad News
Change in covariance	−0.0065	0.0390	0.0077	0.0247	−0.0207	0.0532
Implied risk premium (%pa)	7.809	8.367	7.984	8.192	7.634	8.542
Change in RP(%pa)	−0.080	0.479	0.095	0.304	−0.255	0.654
% change in RP	−1.012	6.068	1.204	3.851	−3.229	8.284

Note: This table shows the effect of a typical market and firm shock on the conditional covariance estimate, and the implied change in risk premium using average parameter estimates. The value of a typical market or firm shock is defined as the average of the absolute standardized residuals from the estimation. Calculation of the average risk premium uses the average conditional covariance over the sample of stocks. The change in risk premium (Change in RP(%pa)) is obtained by subtracting the average stock risk premium (7.88% pa) from the implied risk premium.

gives an estimated average risk premium of 7.888% per annum. We define the average firm shock as the mean of the absolute firm standardized residuals, and the average market shock as the mean of the absolute market standardized residuals. The effect of these typical market and firm shocks on the conditional covariance and the resultant average stock risk premium is summarized in Table 3, which shows the asymmetric effect of news on covariance and consequently average stock risk premium.

Looking at the left-hand side of Table 3, market-level news by itself generates clear asymmetry in covariance and risk premium. Good news at the market level decreases covariance, decreasing the risk premium from 7.89% to 7.81%, a decrease of 8 points and representing a percentage change of about 1%. However, bad news increases covariance substantially more, increasing the annual risk premium to 8.37%, 48 points up, a percentage increase of 6%. This is quite a difference and exists when there is no specific firm news; that is, the market-level news affects the market risk premium and therefore the expected stock premium must also change.

For the effect of firm-specific news, remember that the firm-specific parameter estimates are not consistent in sign and significance in the estimation; therefore, the effect of firm-specific news comes through the joint parameter estimate (θ_{cim}), which is significant across all cases. The right-hand side of Table 3 shows the four combinations, and again, covariance asymmetry is evident.

When firm-specific and market-level news are both good, the effect on the conditional covariance and risk premium is minimal, with an increase of only 10 points—a change of 1.2% from the original figure. Bad news at both levels, however, is substantially different, generating a 65-point increase in the risk premium, a percentage increase of more than 8%. That is, bad news at the market level increases the market risk premium, and bad news at the firm level increases the covariance risk such that the combined effect is considerable.

The other two intermediate possibilities are interesting and demonstrate the full effect of covariance asymmetry. Good news at the firm level and bad news at the market level increase covariance and the required risk premium by 30 points, an increase of almost 4%. However, bad news at the firm level is overpowered by good news at the market level and we see a decrease in the risk premium for the average stock of 25 points, a decrease of around 3%. This result suggests that stocks are priced according to their systematic risk and that a firm's specific risk has little effect and is not significantly priced by the market, thereby providing indirect empirical support for the CAPM.

This analysis shows that negative return shocks, for either the market or firm, increase the risk premium more than do positive return shocks. Note that these results are independent of the actual value used for the market price of risk because the price of risk is a common factor across all calculations. Contrary to the conclusion drawn by Braun, Nelson, and Sunier (1995) that beta cannot account for time-varying risk premiums (and hence mean reversion), we find evidence that conditional covariance can potentially explain time-varying risk premiums, supporting the hypotheses of Chan (1988) and Ball and Kothari (1989) that mean reversion might explained by changing investor expectations in an efficient market.

Volatility Feedback

Our results confirm that conditional covariances respond positively to increases in market volatility at the firm level. In particular, the conditional covariance between market and stock returns is asymmetric in that it responds more to negative than to positive market return shocks so that the volatility feedback effect is particularly strong. Bekaert and Wu (2000), using a multivariate GARCH model, find significant covariance asymmetry in the Japanese market, and our results confirm their findings in the Australian market.

Campbell and Hentschel (1992) find that during normal periods of activity, changing volatility has little effect on the level of stock prices and only during periods of high market volatility does volatility feedback become important. Our results conflict with this view, as we find consistent evidence of significant volatility feedback across all stocks, independent of individual or market volatility.

With regard to the leverage hypothesis put forward by Black (1976) and Christie (1982), our results do not support their claims. The parameter estimates for conditional covariance are consistent across the whole sample, regardless of the degree of leverage existing for the individual firms throughout the sample period. The evidence supports conditional covariance changing expected risk premiums, and hence asset prices, irrespective of individual leverage effects. That is not to say that operating or financial leverage will not affect the magnitude of change, or that it is not a contributing causal factor, but it cannot explain the extent to which asymmetric volatility is observed at the firm level, whereas covariance asymmetry can.

What About Conditional Betas?

Asymmetry in beta is difficult to detect because of the interaction between conditional covariance and conditional volatility in the calculation of conditional beta, particularly because both series show significant asymmetry. We think it is not surprising, therefore, that evidence of beta asymmetry is inconsistent and inconclusive. We propose that detecting beta asymmetry is difficult and not as powerful as detecting covariance asymmetry and we explore this further. Specifically, using the same set of stocks, we employ the econometric methods of Braun, Nelson, and Sunier (1995) and Cho and Engle (1999) to estimate a conditional beta series in an attempt to detect beta asymmetry. We find that the results of both estimations (unreported to conserve space) are similar in terms of parameter estimates and log likelihood values. Most notably, there is little evidence of the conditional beta process varying with market- or firm-level shocks, leading us to conclude that for these models, there is little to support an asymmetric conditional beta and, therefore, no evidence to support the changing risk premium hypothesis of Chan (1988) and Ball and Kothari (1989).

These results contrast those of our proposed model. We conclude, therefore, that the use of conditional beta requires more powerful tests to observe any asymmetric behavior with regard to return shocks. In the absence of such tests, we argue that it is best to explore time-varying premiums using conditional covariance.

Temporal and Cross-Sectional Aggregation

Cho and Engle (1999) suggest that the reason Braun, Nelson, and Sunier (1995) fail to find asymmetry in beta is because Braun, Nelson, and Sunier use monthly portfolio data. This aggregation, both temporal and cross-sectional, may reduce the ability of econometric tests to detect beta asymmetry. To address this issue, we perform the same covariance analysis on weekly data, with two variations: (1) for our sample of individual stocks and (2) for a set of Australian industry portfolio data obtained from Datastream International.

The outcome of this weekly analysis for the sample of individual stocks produces consistent results when compared with the daily analysis (not reported to conserve space).[8] Table 4 provides parameter estimates of the conditional covariance equation for the industry portfolios. Estimates of θ_{cm} and γ_{cm} both indicate that there is statistically significant covariance asymmetry between the portfolio

[8] Details are available from the authors on request.

TABLE 4. Covariance Equation Estimation Results, Weekly Industry Portfolio Data.

Industry	α_{ci}	δ_{ci}	θ_{ci}	γ_{ci}	θ_{cm}	γ_{cm}	θ_{cim}
Banks	1.8659**	0.6574**	−0.2133	−0.1861	−0.8623**	0.7566**	0.4704**
	(5.51)	(10.50)	(−1.90)	(−1.11)	(−5.85)	(3.40)	(3.70)
Basic	1.6623**	0.7362**	−0.0573	−0.0544	−1.4935**	1.2291**	0.2349**
	(12.88)	(36.88)	(−0.74)	(−0.47)	(−15.61)	(7.85)	(3.16)
Beverages	1.5254**	0.6657**	0.0040	−0.6248**	−1.0590**	0.7084**	0.9388**
	(4.66)	(10.32)	(0.02)	(−2.27)	(−5.61)	(2.36)	(4.70)
Building materials	1.3472**	0.7852**	−0.1316	−0.2351	−1.3166**	1.2217**	0.2363**
	(10.92)	(39.63)	(−1.54)	(−1.76)	(−12.81)	(7.07)	(2.54)
Brewers	1.7348**	0.6399**	−0.1903	−0.6771**	−1.1417**	0.9777**	1.3309**
	(4.61)	(9.60)	(−0.82)	(−2.03)	(−4.50)	(2.49)	(4.66)
Cyclical services	2.2640**	0.6356**	−0.2734**	−0.1920	−1.6489**	1.4278**	0.6083**
	(10.27)	(18.00)	(−2.31)	(−1.00)	(−11.88)	(6.12)	(4.76)
Engines and machinery	0.0163	0.9643**	−0.0591	−0.0213	−0.0371	−0.2673**	0.1304**
	(0.88)	(67.30)	(−1.12)	(−0.27)	(−0.78)	(−3.01)	(2.26)
Food processors	0.4108**	0.8479**	−0.0947	0.0719	−0.5526**	−0.1392	0.3824**
	(3.86)	(24.80)	(−1.01)	(0.52)	(−4.56)	(−0.78)	(3.61)
Gas distribution	1.2328**	0.7093**	−0.0418	0.1562	−0.6726**	1.0188**	1.1278**
	(4.59)	(11.26)	(−0.18)	(0.51)	(−2.93)	(2.43)	(3.89)
Gold mining	0.3591**	0.9387**	0.1936	0.2217	−0.6925**	0.5829**	0.5629**
	(3.25)	(53.35)	(1.28)	(0.91)	(−3.49)	(2.22)	(3.37)
Health care	−0.0391**	1.0188**	−0.0485	0.0624	0.0652**	0.0427	0.0781**
	(−16.15)	(129505)	(−1.44)	(1.45)	(2.50)	(1.33)	(16.78)
Insurance	0.0036	0.9855**	−0.0172	−0.2012**	−0.0010	−0.1639**	0.0418**
	(0.35)	(229.95)	(−0.44)	(−2.55)	(−0.03)	(−3.81)	(3.00)
Investment companies	1.3571**	0.7258**	0.0692	0.3776	−0.8613**	0.8649**	0.6429**
	(4.45)	(11.83)	(0.41)	(1.62)	(−4.39)	(2.91)	(3.60)
Medical equipment and	0.5480**	0.7961**	−0.1049	−0.2452	−0.7282**	−0.1179	0.0960
supplies	(5.01)	(20.07)	(−0.67)	(−1.34)	(−5.28)	(−0.61)	(0.95)
Mining	1.7738**	0.7826**	0.0522	0.0456	−1.5186**	1.4349**	0.1902**
	(19.24)	(65.83)	(0.86)	(0.41)	(−21.94)	(11.92)	(2.53)
Miscellaneous finance	0.0006	0.9916**	0.0494	−0.0096	−0.0484	−0.1319**	0.0814**
	(0.08)	(243.77)	(1.50)	(−0.27)	(−1.84)	(−3.54)	(4.38)
Noncyclical consumption	1.3387**	0.7158**	0.0611	−0.1841	−1.0875**	0.5399**	0.3150**
goods	(7.59)	(18.74)	(0.80)	(−1.29)	(−10.54)	(3.38)	(3.45)

(Continued)

TABLE 4. Continued.

Industry	α_{ci}	δ_{ci}	θ_{ci}	γ_{ci}	θ_{cm}	γ_{cm}	θ_{cim}
Nonferrous metals	2.5947**	0.6152**	0.2708	−0.4430	−2.1610**	1.5198**	0.6329**
	(5.78)	(9.42)	(1.06)	(−1.32)	(−7.57)	(3.38)	(2.62)
Oil and gas	1.1868**	0.8147**	−0.0263	−0.3757**	−1.1591**	1.7900**	0.6632**
	(8.28)	(37.55)	(−0.23)	(−1.98)	(−7.84)	(7.08)	(4.58)
Pharmaceuticals	0.0122	1.0070**	0.0153	0.2824**	−0.0806**	−0.0230	0.0534**
	(1.36)	(509.55)	(0.43)	(5.54)	(−2.56)	(−0.89)	(2.67)
Resources	1.7799**	0.7798**	0.0296	−0.1575	−1.6293**	1.7669**	0.2077**
	(23.03)	(79.84)	(0.56)	(−1.56)	(−25.22)	(15.60)	(3.27)
Railroad and freight	−0.0291**	1.0060**	0.0022	−0.0553**	0.0613**	0.0162	−0.0149**
	(−9.68)	(267.58)	(0.05)	(−2.89)	(2.83)	(0.72)	(−4.77)
Retail	0.0863	0.9873**	−0.0601	−0.0072	0.1333	0.2343**	0.0372
	(0.96)	(57.49)	(−0.43)	(−0.07)	(1.72)	(3.25)	(0.50)
Telecom, media, and information technology	3.0518**	0.5842**	−0.2265	−0.4911	−1.9424**	1.8568**	1.2860**
	(7.34)	(10.35)	(−1.12)	(−1.55)	(−7.98)	(4.36)	(5.41)
Tobacco	0.7750**	0.6578**	−0.7484**	0.5100**	−0.3448**	−0.0780	0.3407
	(3.95)	(7.50)	(−3.98)	(2.06)	(−2.12)	(−0.27)	(1.91)
Utilities	1.1653**	0.7253**	−0.0760	0.2339	−0.7014**	0.9301**	1.0905**
	(4.66)	(12.43)	(−0.33)	(0.77)	(−3.11)	(2.29)	(3.86)
Average	1.0601	0.8054	−0.0626	−0.1048	−0.8162	0.6963	0.4344
p-value	(0.0000)	(0.0000)	(0.0443)	(0.0447)	(0.0000)	(0.0000)	(0.0000)
p-value	[0.0000]	[0.0000]	[0.2812]	[0.0311]	[0.0003]	[0.0119]	[0.0000]

Note: This table shows the simultaneous estimates using weekly data for industry portfolios over the period January 5, 1988, to November 25, 1999. Parameters are estimated by maximum likelihood using the system of equations (5), (6) and (7) in the text. The covariance specification is given by:

$$\sigma_{im,t} = \alpha_{ci} + \delta_{ci}[\sigma_{im,t-1} - \alpha_{ci}] + \Phi(z_{m,t-1}) + \Phi(z_{i,t-1}) + \theta_{cim} z_{m,t-1} z_{i,t-1}, \tag{5}$$

where

$$\Phi(z_{k,t-1}) = \theta_{ck} z_{k,t-1} + \gamma_{ck}[|z_{k,t-1}| - E|z_k|],\ k = i, m, \tag{6}$$

where $\sigma_{im,t}$ is the estimated conditional covariance, $z_{m,t}$ is the standardized residual for the market portfolio, $z_{i,t}$ is the standardized residual for the industry portfolio. Error terms are assumed to follow the generalized error distribution (GED) of Nelson (1991). In relation to individual parameter estimates, the t-statistic is provided in parentheses below the estimated value. In relation to overall averages, the p-value for the cross-sectional t-test (nonparametric sign test) for the hypothesis that the average parameter estimate is equal to zero is provided in parentheses (square brackets) below the reported average.

** Significant at the 5% level.

and market returns. This is consistent across all portfolios and we conclude, again, that there is evidence supporting the changing risk premium hypothesis for asymmetric volatility. Once more the results are independent of the level of leverage that exists across the individual portfolios; therefore, we find little evidence to support the leverage hypothesis.

VI. Conclusion

In this article we investigate whether conditional covariance increases with bad news and decreases with good news, as does volatility. We employ both daily returns for individual stocks and weekly industry portfolios for Australian equity data from January 5, 1988, to November 25, 1999, using a simultaneously estimated EGARCH specification.

Our primary motivation is the observed asymmetric volatility and mean reversion of stock prices through time-varying risk premiums. We approach the issue of time-varying expected returns not through beta, but through decomposing the artificial construct of beta and examining time-varying covariances directly. We find consistent evidence that time-varying risk premiums can be accounted for by changing covariance and we identify significant asymmetry in the conditional covariance response to good and bad news. Moreover, we consistently observe this asymmetry across both daily and weekly returns, individual firms and aggregated portfolios, irrespective of size or leverage. This observed asymmetry in conditional covariance also supports the volatility feedback hypothesis of Pindyck (1984).

Our empirical results are important in explaining volatility asymmetry at the firm level, suggesting that the causal effect is through asymmetric conditional covariance. Our results support the notion that asymmetric covariance affects the variance process of individual stocks, and we find little evidence in support of the leverage hypothesis of Black (1976) and Christie (1982). Furthermore, we show that the use of conditional beta in estimating time-varying risk premiums can be inconclusive and that conditional covariance is a superior instrument for examining such issues.

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