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ASYMMETRIC VOLATILITY AND RISK IN EQUITY MARKETS

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ABSTRACT

It appears that volatility in equity markets is asymmetric: returns and conditional volatility are negatively correlated. We provide a unified framework to simultaneously investigate asymmetric volatility at the firm and the market level and to examine two potential explanations of the asymmetry: leverage effects and time-varying risk premiums. Our empirical application uses the market portfolio and portfolios with different leverage constructed from Nikkei 225 stocks, extending the empirical evidence on asymmetry to Japanese stocks. Although volatility asymmetry is present and significant at the market and the portfolio levels, its source differs across portfolios. We find that it is important to include leverage ratios in the volatility dynamics but that their economic effects are mostly dwarfed by the volatility feedback mechanism. Volatility feedback is enhanced by a phenomenon that we term covariance asymmetry: conditional covariances with the market increase only significantly following negative market news. We do not find significant asymmetries in conditional betas.

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1. INTRODUCTION

There is a long tradition in finance (see for example Cox and Ross (1976)) that models stock return volatility as negatively correlated with stock returns. Influential papers by Black (1976) and Christie (1982) further document and attempt to explain the asymmetric volatility property of individual stock returns in the U.S. The explanation put forward in these papers is based on leverage. A drop in the value of the stock (negative return) increases financial leverage, which makes the stock riskier and increases its volatility[1].

Although to many "leverage effects" have become synonymous to asymmetric volatility, the asymmetric nature of the volatility response to return shocks could simply reflect the existence of time-varying risk premiums (Pindyck, (1984), French, Schwert and Stambaugh, (1987) and Campbell and Hentschel (1992)). If volatility is priced, an anticipated increase in volatility raises the required return on equity, leading to an immediate stock price decline. Hence the causality is different: the leverage hypothesis claims that return shocks lead to changes in conditional volatility whereas the time varying risk premium theory contends that return shocks are caused by changes in conditional volatility.

Which effect is the main determinant of asymmetric volatility remains an open question. Studies focusing on the leverage hypothesis, such as Christie (1982) and Schwert (1989), typically conclude that it cannot account for the full volatility responses. Likewise, the time-varying risk premium theory enjoys only partial success. The volatility feedback story relies first of all on the well-documented fact that volatility is persistent. That is, a large realization of news, positive or negative, increases both current and future volatility. The second basic tenet of this theory is that there exists a positive intertemporal relation between expected return and conditional variance. The increased volatility then raises expected returns and lowers current stock prices, dampening volatility in the case of good news and increasing volatility in the case of bad news. Whereas such a relationship for the market portfolio would be consistent with the Capital Asset Pricing Model (CAPM, Sharpe (1964)), it only holds in general equilibrium settings under restrictive assumptions (see Backus and Gregory (1992), Campbell (1993) and the discussion in Glosten, Jagannathan and Runkle (1993)).

Moreover, there are conflicting empirical findings. For example, French, Schwert and Stambaugh (1987) and Campbell and Hentschel (1992) find the relation between volatility and

[1] Black (1976) also discusses an operating leverage effect, induced by fixed costs of the firm, but that effect has received little attention in the finance literature.

expected return to be positive while Turner, Startz and Nelson (1989), Glosten, Jagannathan and Runkle (1993) and Nelson (1991) find the relation to be negative. If the relation between market conditional volatility and market expected return is not positive, then the validity of the time varying risk premium story is in doubt.

Furthermore, the time varying risk premium story does not readily explain the existence of volatility asymmetry at the firm level, since, in the CAPM example, the relevant measure of risk is then the covariance with the market portfolio. For the time-varying risk premium story to explain firm-specific volatility asymmetry, covariances with the market portfolio should respond positively to increases in market volatility.

Our first contribution is to develop a general empirical framework to examine volatility asymmetry at the market level and at the firm or portfolio level simultaneously and to differentiate between the two competing explanations. That such an analysis has not be done before reflects the existence of two virtually separate literatures. As the survey of empirical papers in Table 1 shows, studies focusing on the time-varying risk premium story typically use market level returns, whereas studies focusing on the leverage hypothesis typically use firm or portfolio data. Moreover, the empirical specifications are not entirely compatible across the two literatures. Studies focusing on individual firms typically use regression analysis to examine the relation between a measure of volatility during a particular month ("gross" volatility) and the return in the previous month. Studies at the market level have mostly used the GARCH-in-mean framework of Engle, Lilien and Robbins (1987) focusing on the relation between return innovations and the conditional volatility of the returns (See Table 1).

Our second contribution is to document a new phenomenon that helps explain volatility asymmetry at the firm level: covariance asymmetry. When the conditional covariance between market and stock returns responds more to negative than to positive market shocks the volatility feedback is particularly strong. Our empirical framework accommodates this possibility and we find evidence of such covariance asymmetry. Although Kroner and Ng (1995) document covariance asymmetry in the volatility dynamics of portfolios of small and large firms, most previous studies have focused on asymmetric effects in conditional betas (see Braun, Nelson and Sunier (1995), Ball and Kothari (1989)) with conflicting empirical results. We argue below that asymmetry is more likely to be found in conditional covariances and re-examine whether conditional betas display asymmetry for our sample. We also compare the fit of our model to that of unconditional and rolling beta models.

Our third contribution is to re-examine potential size effects in the asymmetry relation. Cheung and Ng (1992) show that volatility asymmetry is stronger for small U.S. firms, without providing an explanation. In fact, this may not be surprising. First, Christie's (1982) classic analysis implies that the negative relation between current returns and future volatility is stronger for firms with higher financial leverage and small firms may have higher leverage. Second, small firms may have higher betas and higher beta stocks may exhibit stronger covariance asymmetry[2].

Finally, we hope that our analysis will contribute to a more widespread use of asymmetric volatility in financial modelling. In the extensive GARCH-literature, a number of sophisticated models have been developed to accommodate asymmetric volatility (see e.g. Nelson (1991), Glosten, Jagannathan and Runkle (1993) and Hentschel (1995)) and the results in Pagan and Schwert (1990) and Engle and Ng (1993) indicate that these volatility models outperform standard GARCH models. Nevertheless, most applications of GARCH models, with a few exceptions, have not yet embraced asymmetric volatility models. For example, parameterizations of CAPM models that use GARCH (see e.g. Engel, Frankel, Froot and Rodriguez (1995)), models of volatility spill-over across equity markets (see e.g. Hamao, Masulis and Ng (1990))) and stochastic volatility models for options (Hull and White (1987)) have typically not used asymmetric volatility models[3]. One would expect these models to yield quite different conditional volatilities from symmetric GARCH models. Whereas most of the empirical analysis so far (see Table 1) has focused on U.S. stock returns, our empirical application focuses on the market return and portfolio returns constructed from Japanese stocks in the Nikkei index. Our results indicate that asymmetry is an important feature of stock market volatility in the Japanese market as well.

The remainder of the article is organized as follows. Section 2 formulates our empirical model, the empirical hypothesis and explains the role of leverage in generating asymmetric risk and volatility. A set of specification tests is also discussed. Section 3 discusses the data and the empirical results. Section 4 looks for a size effect in asymmetric volatility and the final section concludes the paper.

2 Duffee (1995) documents a puzzling strong positive relation between returns and contemporaneous volatility, which is stronger for small firms.

3 Exceptions are Koutmos and Booth (1995) and Ng (1996) in the volatility spillover literature and Duan (1995), Amin and Ng (1993) and Wu (1997) in the options literature.

2. A MODEL OF ASYMMETRIC VOLATILITY AND RISK

2.1 Asymmetric Volatility and Risk at the Firm and Market Level

To establish notation, let $P_{M,t}$ denote the market index, let $r_{M,t}$ denote the return of the market portfolio and $r_{M,t+1} = E\left(r_{M,t+1}|I_t\right) + \epsilon_{M,t+1}$ where I_t denotes the information set at time t. Similarly, $P_{i,t},\ r_{i,t}$ are the price and return of the stock of firm i respectively and $r_{i,t+1} = E(r_{i,t+1}|I_t) + \epsilon_{i,t+1}$. Define conditional variances and covariances, $\sigma^2_{M,t+1} = var(r_{M,t+1}|I_t), \sigma^2_{it+1} = var(r_{i,t+1}|I_t)$ and $\sigma_{iM,t+1} = cov(r_{i,t+1}, r_{M,t+1}|I_t)$.

Definition: A return $r_{i,t}$ displays *asymmetric volatility* if

$$\text{var}\left[r_{i,t+1}|I_t, \epsilon_{i,t} < 0\right] - \sigma^2_{i,t} > \text{var}\left[r_{i,t+1}|I_t, \epsilon_{i,t} > 0\right] - \sigma^2_{i,t} \tag{1}$$

In words, negative unanticipated returns result in an upward revision of the conditional volatility whereas positive unanticipated returns result in a smaller upward or even a downward revision of the conditional volatility[4].

One explanation for such asymmetry at the equity level relies on changes in leverage. To illustrate, consider a world where debt is riskless, that is, the return on all debt equals the risk free rate. We denote the risk free rate by $r^f_{t-1,t}$, since it is known at $t-1$. It is straightforward to show that

$$r_{i,t} - r^f_{t-1,t} = \left(1 + LR_{i,t-1}\right)\left(\overline{r}_{i,t} - r^f_{t-1,t}\right) \tag{2}$$

where $LR_{i,t-1}$ is the leverage ratio for firm i and $\overline{r}_{i,t}$ refers to the return on the firm's assets. Even when the volatility of the return on a firm's assets is constant, the conditional volatility of the equity return should change when leverage changes (see also Christie (1982) and Schwert (1989)). In particular, shocks that increase the value of the firm, reduce leverage and, with it, the conditional volatility of the stock's return and vice versa. We use the riskless debt model to illustrate leverage effects throughout the article but our empirical specification is valid more generally.

Our analysis here is premised on two assumptions, which we test below. First, we assume that a conditional version of the CAPM holds, i.e., the market portfolio's expected excess return is the (constant) price of risk times the conditional variance of the market and the expected excess

[4] We will refer to the latter case as "strong asymmetry," which implies

$$\begin{aligned} \text{var}\left[r_{t+1}|I_t, \epsilon_t > 0\right] - \sigma^2_t &< 0, \quad \textit{and} \\ \text{var}\left[r_{t+1}|I_t, \epsilon_t < 0\right] - \sigma^2_t &> 0. \end{aligned}$$

return on any firm is the price of risk times the conditional covariance between the firm's return and the market. Note that we formulate the volatility feedback effect at the level of the firm's total assets, since it does not at all depend on leverage. Second, we assume that conditional volatility is persistent, which is an empirical fact supported by extensive empirical work, see Bollerslev, Chou and Kroner (1992). Since the time variation in second moments is not restricted by the CAPM, we explicitly parameterize it in the next subsection. For now, we consider more generally the mechanisms generating asymmetry, including leverage and volatility feedback, at the market level and firm level using the flow chart in Figure 1.

We begin by considering news (shocks) at the market level. Bad news at the market level has two effects. First, whereas news is evidence of higher current volatility in the market, investors also likely revise the conditional variance since volatility is persistent. According to the CAPM, this increased conditional volatility at the market level has to be compensated by a higher expected return, leading to an immediate decline of the current value of the firm and the stock price and a further return shock to the market. The price decline will not cease until the expected return is sufficiently high. Hence, a negative return shock may generate a significant increase in conditional volatility. Second, the market-wide price decline (a negative return shock) leads to higher leverage at the market level and hence higher stock volatility. That is, the leverage effect reinforces the volatility feedback effect. Note that although the arrows in Figure 1 suggest a sequence of events, the effects described above happen simultaneously, that is, leverage and feedback effects interact.

When good news arrives in the market, there are again two effects. First, news brings about higher current period market volatility and an upward revision of the conditional volatility. When volatility increases, prices decline to induce higher expected returns, offsetting the initial price movement. The volatility feedback effect dampens the original volatility response. Second, the resulting market rally (positive return shock) reduces leverage and decreases conditional volatility at the market level. Hence, the net impact on stock return volatility is not clear.

As Figure 1 shows, for the initial impact of news at the firm level, the reasoning remains largely the same: bad and good news generate opposing leverage effects which reinforce (offset) the volatility embedded in the bad (good) news event. What is different is the volatility feedback. A necessary condition for volatility feedback to be observed at the firm level is that the covariance of the firm's return increases in response to market shocks. If the shock is completely idiosyncratic, the covariance between the market return and individual firm return should not change, and no change in the required risk premium occurs. Hence, idiosyncratic shocks generate volatility asymmetry purely through a leverage effect. Volatility feedback at the firm level occurs when market-wide shocks increase the covariance of the firm's return with the market. Such covariance behavior would be implied by a CAPM model with constant firm betas and seems generally plausible. The impact on the conditional covariance is likely to be different across firms. For firms with high systematic risk, market-wide shocks may significantly increase their conditional covariance with the market. The resulting higher required return then leads to a volatility feedback effect on the conditional volatility, which would be absent or weaker for firms less sensitive to market level shocks. From equation (2), it also follows that any volatility feedback effect at the firm level leads to more pronounced feedback effects at the stock level, the more leveraged the firm is.

The volatility feedback effect would be stronger if covariances respond asymmetrically to market shocks. We call this phenomenon *covariance asymmetry*. So far, covariance asymmetry has primarily received attention in the literature on international stock market linkages, where larger co-movements of equity returns in down markets adversely affect the benefits of international diversification (Das and Uppal (1996)). Kroner and Ng (1995) document covariance asymmetry in stock returns on U.S. portfolios of small and large firms without providing an explanation. However, covariance asymmetry in stock returns could be partially explained by a pure leverage effect, without volatility feedback. Using the riskless debt model, it follows

$$\begin{aligned} cov_{t-1}\left[r_{i,t} - r^f_{t-1,t}, r_{M,t} - r^f_{t-1,t}\right] &= (1 + LR_{i,t-1})\,(1 + LR_{M,t-1}) \\ &\quad cov_{t-1}\left[\overline{r}_{i,t} - r^f_{t-1,t}, \overline{r}_{M,t} - r^f_{t-1,t}\right]. \end{aligned} \tag{3}$$

Even with constant covariance at the firm level, the covariance of an individual stock return with the market may exhibit (strong) asymmetry. Conditional stock return betas are somewhat less likely to display pure leverage effects, since

$$\beta_{i,t-1} = \frac{1 + LR_{i,t-1}}{1 + LR_{M,t-1}}\overline{\beta}_{i,t-1}, \tag{4}$$

where $\overline{\beta}_{i,t-1}$ ($\beta_{i,t-1}$) is the firm (stock) beta. Hence, idiosyncratic shocks should result in asymmetric beta behavior, but the effect of market-wide shocks on betas is ambiguous.

At the firm level as well, covariance asymmetry arises more naturally than beta asymmetry. Suppose the conditional beta of a firm is positive but constant over time, still a popular assumption in many asset pricing models. Then the conditional covariance with the market return is proportional to the conditional variance of the market. Hence a market shock that raises the market's conditional variance increases the required risk premium on the firm (unless the price of risk changes) and causes a volatility feedback effect. When the effect of the market shock on market volatility is asymmetric, the firm (and stock) return automatically displays covariance asymmetry. Of course, betas do vary over time (see Jagannathan and Wang (1995) for a recent discussion) and may exhibit asymmetry as well, but it is hard to come up with a natural story for beta asymmetry at the firm level. In the framework set out below, we impose only mild restrictions on the behavior of betas over time and we examine whether they exhibit asymmetry.

2.2 Empirical Model Specification

We use a conditional version of the CAPM to examine the interaction between the means and variances of individual stock returns and the market return. The conditional mean equations are defined as

$$\begin{cases} r_{M,t} - r^f_{t-1,t} = Y_{t-1}\sigma^2_{M,t} + \epsilon_{M,t} \\ r_{1,t} - r^f_{t-1,t} = Y_{t-1}\sigma_{1M,t} + \epsilon_{1,t} \\ \vdots \quad \vdots \quad \vdots \\ r_{n,t} - r^f_{t-1,t} = Y_{t-1}\sigma_{nM,t} + \epsilon_{n,t} \end{cases} \tag{5}$$

where $r^f_{t-1,t}$ is the one period risk free interest rate known at time $t-1$, Y_{t-1} is the price of risk, M denotes the market portfolio, and n is the number of other portfolios included in the study. Naturally, these portfolios are classified by the leverage ratios of the underlying firms, with portfolio 1 having the highest leverage and portfolio n the lowest. We call these portfolios the leverage portfolios.

The time variation in the price of risk depends on market leverage:

$$Y_{t-1} = \frac{Y}{1 + LR_{M,t-1}}. \tag{6}$$

This specification for the price of risk follows from formulating the CAPM at the firm level, not the equity level, with a constant price of risk. That is,

$$Y = \frac{E_{t-1}\left[\overline{r}_{M,t}\right] - r^f_{t-1,t}}{\overline{\sigma}^2_{M,t}}, \tag{7}$$

where the bars indicate firm values, rather than equity values. Under certain assumptions, Y is the aggregate coefficient of relative risk aversion (see Campbell (1993)). It is critical in this context that the return used in equation (7) is a good proxy to the return on the aggregate wealth portfolio. Since the stock index we use in the empirical work is highly levered, $\overline{r}_{M,t}$ is a better proxy[5] than $r_{M,t}$. Of course, the specification in equation (6) relies on the riskless debt model. However we

[5] Jagannathan, Kubota and Takehara (1996) argue that a portfolio of listed stocks is unlikely to be a good proxy for the aggregate wealth portfolio in Japan and find that labor income is priced. They ignore leverage effects, however.

subject the model to a battery of specification tests some of which are specifically designed with alternatives to the riskless debt model in mind. We also estimate a model in which the price of risk is assumed constant at the stock market level for comparison.

Since the CAPM does not restrict the time-variation in second moments, we employ a multivariate GARCH model. Specifically, the variance-covariance matrix follows an asymmetric version of the BEKK model (Engle and Kroner (1995) and Kroner and Ng (1995)). This GARCH-in-mean parameterization of the CAPM, incorporating an equation for the market portfolio, is similar to the international CAPM parameterization in Bekaert and Harvey (1995) and DeSantis and Gerard (1996), with more general volatility dynamics.

Define,

$$\epsilon_t = \begin{pmatrix} \epsilon_{M,t} \\ \epsilon_{1,t} \\ \vdots \\ \epsilon_{n,t} \end{pmatrix}, \eta_t = \begin{pmatrix} \eta_{M,t} \\ \eta_{1,t} \\ \vdots \\ \eta_{n,t} \end{pmatrix}, \eta_{i,t} = \begin{cases} -\epsilon_{i,t} & \text{if } \epsilon_{i,t} < 0 \\ 0 & \text{otherwise} \end{cases} \quad \forall i \tag{8}$$

The asymmetric shocks η may capture both a volatility feedback effect and a leverage effect. Consistent with our analysis of asymmetric volatility in Section 2.1, we also introduce leverage ratios for both the market portfolio and the leverage portfolios into the conditional variance process to capture leverage effects more directly,

$$l_t = \begin{pmatrix} LR_{M,t} \\ LR_{1,t} \\ \vdots \\ LR_{n,t} \end{pmatrix},$$

where LR represents the leverage ratio. The conditional variance covariance matrix is

$$\Sigma_t = E\left(\epsilon_t \epsilon_t' | I_{t-1}\right) = \begin{pmatrix} \sigma^2_{M,t} & \sigma_{M1,t} & \cdots & \sigma_{Mn,t} \\ \sigma_{M1,t} & \sigma^2_{1,t} & \cdots & \sigma_{1n,t} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{Mn,t} & \sigma_{1n,t} & \cdots & \sigma^2_{n,t} \end{pmatrix} \tag{9}$$

which is modeled as

$$\Sigma_t = \Omega\Omega' + B\Sigma_{t-1}B' + C\,\epsilon_{t-1}\epsilon'_{t-1}C' + D\,\eta_{t-1}\eta'_{t-1}D' + G\,l_{t-1}l'_{t-1}G'. \tag{10}$$

In "VEC" notation the model becomes

$$\text{VEC}(\Sigma_t) = \Omega^* + B^*\text{VEC}(\Sigma_{t-1}) + C^*\text{VEC}(\epsilon_{t-1}\epsilon\prime_{t-1}) + D^*\text{VEC}(\eta_{t-1}\eta\prime_{t-1}) + G^*\text{VEC}(l_{t-1}l\prime_{t-1}), \tag{11}$$

with $\Omega^* = VEC(\Omega\Omega')$, $B^* = B \otimes B$, $C^* = C \otimes C$, $D^* = D \otimes D$ and $G^* = G \otimes G$. Ω, B, C, D and G are $n+1$ by $n+1$ constant matrices, with elements ω_{ij} and b_{ij} , etc. The conditional variance and covariance of each excess return are related to past conditional variances and covariances, past squared residuals and cross residuals, past squared asymmetric shocks and cross asymmetric shocks, and past leverages and cross leverages of all portfolios[6].

Apart from its technical advantages that simplify estimation (see Engle and Kroner (1993), the BEKK model has quite general volatility dynamics. Alternative multivariate GARCH models impose restrictions on the variance process that make them ill-suited for our purposes. The (diagonal) VECH model (Bollerslev, Engle and Wooldridge, 1988) cannot capture volatility feedback effects at the firm level. The Factor ARCH model (Engle, Ng and Rothschild, 1990) assumes that the covariance matrix is driven by the conditional variance process of one portfolio (the market portfolio), making it impossible to test for firm-specific leverage effects. The Constant Correlation model (Bollerslev, 1990) restricts the correlation between two asset returns to be constant over time. Braun, Nelson and Sunier (1995) use univariate asymmetric GARCH models coupled with a specification for the conditional beta that accommodates asymmetry. As we suggest above, it is more natural to model asymmetry in covariances, as is possible in the BEKK framework.

One drawback of the BEKK model is the large numbers of parameters that must be estimated. For a system of m equations, there are $(9m^2 + m + 2)/2$ parameters. For example, a system of 4 equations has 75 parameters. To keep the size of the parameter space manageable, we impose additional constraints. We assume that lagged market level shocks and variables enter all conditional variance and covariance equations, but that individual portfolio shocks and variables have explanatory power only for their own variances and covariances with the market.

The parameter matrices B, C, D and G now have the form, for example,

$$B = \begin{pmatrix} b_{MM} & 0 & 0 & \cdots & 0 \\ b_{M1} & b_{11} & 0 & \cdots & 0 \\ b_{M2} & 0 & b_{22} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 \\ b_{Mn} & 0 & 0 & \cdots & b_{nn} \end{pmatrix}.$$

This reduces the parameter space considerably while leaving enough flexibility in modeling the processes of all conditional variances and covariances with the market. For a system of 4 equations, there are 39 parameters, instead of 75.

[6] Note that the asymmetric shock is defined using the negative shocks as opposed to Glosten, Jagannathan and Runkle (1993), who use positive shocks. This is consistent with the idea that the strong form of asymmetric volatility, discussed above, is most likely to arise from the direct leverage effect, through the l_t variable.

2.3 Empirical Hypotheses

2.3.1 Asymmetry, Volatility Feedback and Leverage

Asymmetric volatility in the model enters through the η- terms and the leverage ratios. To test for the significance of asymmetry, we test the hypothesis $D = 0, G = 0$. Since previous GARCH models of asymmetry have not added leverage ratios to the conditional variance equation, we also test $G = 0$ separately. Finally, since in the literature on firm volatility, firm volatility is linked exclusively to leverage ratios, we test the hypotheses $D = 0$ (GARCH with leverage effects fully captured by leverage ratios) and $B = 0,\ C = 0,\ D = 0$ (volatility changes completely driven by changes in leverage). In the latter case, the volatility model is still more general than earlier leverage models of volatility. In a world where the variance of the firm's asset is constant and the firm has riskless debt, the relation between the leverage and conditional stock volatility is trivial:

$$\sigma^2_{i,t+1} = (1 + LR_{i,t})^2 \cdot \overline{\sigma}^2_i \quad for\ i = 1, \ldots, n \tag{12}$$

If $B = C = D = 0$, our volatility model reduces to:

$$\sigma^2_{i,t+1} = c + v^2 LR^2_{M,t} + 2vw LR_{M,t} LR_{i,t} + w^2 LR^2_{i,t} \tag{13}$$

When $v = 0$, the model is closely related to the leverage model above since $(1 + LR_{i,t})^2$ and $1 + {LR_{i,t}}^2$ are extremely highly correlated[7].

Equation (13) also reveals the difficulty in disentangling volatility feedback and leverage effects. When a market shock occurs, we expect most of the volatility feedback effect to work through $\epsilon_{M,t}$ and $\eta_{M,t}$ but (13) shows that the market leverage ratio could partially capture a volatility feedback effect as well. Conversely, the $\eta_{i,t}$ shocks could capture both volatility feedback effects (if part of the shock is a market shock) or leverage effects (when it is primarily an idiosyncratic shock). One way to keep these two effects separate is to further restrict the D and G matrices as follows:

$$D^R = \begin{pmatrix} d_{MM} & 0 & 0 & \cdots & 0 \\ d_{M1} & 0 & 0 & \cdots & 0 \\ d_{M2} & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 \\ d_{Mn} & 0 & 0 & \cdots & 0 \end{pmatrix}, \quad G^R = \begin{pmatrix} g_{MM} & 0 & 0 & \cdots & 0 \\ 0 & g_{11} & 0 & \cdots & 0 \\ 0 & 0 & g_{22} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & \cdots & g_{nn} \end{pmatrix}.$$

With this model, the LR_t variables capture leverage effects and the η_t variables capture volatility

[7] For the portfolios used in our empirical work that correlation is never below 99%. Christie (1982), generalizing the leverage model to risky debt, finds that $\sigma_{i,t} = \beta_0 + \beta_1 LR_{i,t}$, and the ratio β_1/β_0 should decline as leverage increases. He finds empirical support for this hypothesis, using simple regression analysis. Although our volatility model does not exactly nest Christie's equation, even the restricted model in (13) suggests that his regression may suffer from omitted variable bias.

feedback effects. If both effects are present and interaction effects are important, as our analysis in Section 2.1 suggests, this model may be rejected. We test this restricted model with a likelihood ratio test below. Nevertheless, the parameter changes relative to the full model may be informative about the source of the volatility asymmetry captured by the η_t terms.

To gain further insight into the relative importance of feedback effects versus leverage effects across leverage portfolios, we make use of the news impact curves introduced by Engle and Ng (1993), generalized to accommodate the effects of the leverage ratio variables. The news impact curve graphs the conditional variance as a function of the shocks, keeping the other inputs to the conditional variance equation (conditional variances and co-variances) constant at their unconditional means. We call the effect of the ϵ and η shocks the "direct effect". Of course, our variance equation also incorporates leverage ratios. We augment the news impact curves with the effect of changes in leverage using a second order Taylor approximation to the non-linear relation between leverage ratios and shocks, evaluated at the sample mean[8]. We then split up this curve into two pieces. First, we look at the news impact curve from market shocks and market leverage ratios, assuming zero portfolio shocks. This curve unambiguously reflects volatility feedback. Second, we investigate the impact of portfolio shocks and portfolio leverage, assuming zero market shocks. This curve may reflect both leverage effects and volatility feedback, and we discuss the likely source of the effects below. These curves ignore interaction effects due to the presence of terms such as $\eta_i\eta_M$ and LR_iLR_M in the conditional variance equation. Hence, we also provide a three dimensional news impact surface as in Kroner and Ng (1995), that incorporates these interaction effects.

Finally, the estimated parameters are directly informative about the relative importance of market versus portfolio shocks. With the $M(i)$ subscript denoting the market (firm), volatility asymmetry at the market level implies

$$\frac{\partial \sigma^2_{M,t+1}}{\partial \eta^2_{M,t}} > 0.$$

In our framework, this can be tested by testing whether $D^*_{MM} > 0$. In addition, we expect

$$\frac{\partial \sigma^2_{M,t+1}}{\partial LR^2_{M,t}} > 0,$$

that is $G^*_{MM} > 0$. For the leverage portfolios, we can gauge the statistical significance of volatility

[8] Since we compute returns as the logarithm of gross returns, the level of leverage ratio as a function of the return shock is

$$LR(\epsilon_t) = LR(\epsilon_t = 0)\left[1 + \epsilon_t^2 - \epsilon_t\right],$$

where $LR(\epsilon_t = 0)$ is evaluated at the sample mean of leverage ratios.

feedback, ignoring the direct effect of a change in market leverage and a potential indirect effect through firm specific shocks, by testing

$$\frac{\partial \sigma^2_{i,t+1}}{\partial \eta^2_{M,t}} > 0.$$

This is equivalent to testing $D^*_{iM} > 0$.

2.3.2 Covariance and Beta Asymmetry

As noted above, a necessary condition to observe volatility feedback at the firm level is that covariances increase more when the shock is negative than when it is positive. This is directly testable using the parameter estimates. We also test for co-variance asymmetry and produce news impact curves and surfaces for the covariances. We investigate whether covariance asymmetry translates into strong volatility feedback effects and whether it is more pronounced for firms with high systematic risk[9].

Given that most recent research has focused on asymmetries in betas, we examine whether the conditional betas implied by our model exhibit leverage effects. To do so, we create approximate news impact surfaces for the β's. This can be accomplished by combining the impact of shocks on conditional variances and covariances.

The idea of a leverage effect in betas received recent attention in the literature on stock market over-reaction. Ball and Kothari (1989) and Chan (1989) show that betas of loser portfolios increase and betas of winner portfolios decrease, providing a potential explanation for the observed reversal in performance. Both articles ascribe the beta change to the effect of negative return shocks on leverage, which in turn increases beta. This behavior is implied by idiosyncratic shocks in the riskless debt model. In our volatility model, the link between betas and leverage is less direct. However, implicitly betas are a non-linear function of leverage ratios and return shocks. In addition to our news impact curves, we examine the link with past returns more directly by running the regression,

$$\beta_{i,t} = \alpha + k_J \sum_{j=1}^{J} [r_{i,t-j} - r_{M,t-j}] + \epsilon_{i,t} \tag{14}$$

where J is the window size. The work of Ball and Kothari (1989) predicts k_J to be negative. Our analysis suggests that k_J should be negative for portfolios (or time periods) where idiosyncratic

[9] Note that the BEKK-model imposes non-linear restrictions on the parameters, which implies that covariances and variances are partially driven by the same parameters. Nevertheless, it is possible for the model to generate volatility asymmetry in response to market shocks without generating covariance asymmetry or to simultaneously generate reverse covariance asymmetry. Consistent with the volatility feedback model, the strength of covariance and volatility asymmetry is positively correlated when the parameter D_{iM} is positive.

shocks dominate (See also equation (4)).

2.4 Specification Tests

2.4.1 Generic Tests

We conduct tests of the specification of the conditional means, variances and covariances. These tests are indicated by MEAN, VAR, and COV, respectively. All tests use the standardized residuals: z_t, which are computed as $\left(P_t'\right)^{-1}\epsilon_t$, with $\Sigma_t = P_t' P_t$. That is, z_t is a $N(0, I)$ vector conditional on time $t-1$ information and the model being well specified. For each test and most other tests below we use the generalized method of moments (Hansen 1982) to test moment implications of a well-specified model, which are of the general form:

$$E[V_t | I_{t-1}] = 0$$

with V_t a vector stochastic process. The resulting test statistic has an asymptotic χ^2 distribution with degrees of freedom equal to the dimension of V_t. The use of estimated residuals and the size of our sample may imply that the actual small sample distribution of the test statistics is no longer a χ^2- distribution. Monte Carlo results in Bekaert and Harvey (1997) suggest that the small sample distribution of the tests may have more mass in the right tail so that we over-reject at the asymptotic critical values.

The conditional mean test, MEAN, sets

$$V_t = \begin{bmatrix} z_{it} \\ z_{it} \cdot z_{it-j} \end{bmatrix} j = 1, 2, 3; \quad i = M, 1, 2, 3.$$

MEAN tests the serial correlation properties of the standardized residuals and is done for each portfolio separately.

For the conditional variance tests, VAR, we introduce the variable $q_{i,t} = z_{i,t}^2 - 1$ and we let

$$V_t = \begin{bmatrix} q_{it} \\ q_{it} \cdot q_{it-j} \end{bmatrix} j = 1, 2, 3; \quad i = M, 1, 2, 3.$$

Again the test is done separately for the different portfolios. Finally, to test the conditional covariance specification, consider the variable

$$W_{i,t} = \frac{\epsilon_{i,t}\epsilon_{M,t}}{\sigma_{iM,t}} - 1 \quad i = 1, 2, 3.$$

We let

$$V_t = \begin{bmatrix} W_{it} \\ W_{it} \cdot W_{it-j} \end{bmatrix} j = 1, 2, 3;$$

for each portfolio i.

2.4.2 Testing the CAPM Assumption

The MEAN test partially tests the CAPM assumption. If other risks are priced, the mean of the residual may not be zero. However, this test may not be powerful to detect particular deviations from the CAPM and we provide a number of alternative tests. Our first CAPM test, $CAPM_1$, provides a simple test of whether leverage plays a role in the conditional mean. Bhandari (1988) shows that leverage is cross-sectionally priced in US stock returns. Moreover, if debt is not riskless, leverage ratios may enter the conditional mean.

We put

$$V_t = \begin{bmatrix} z_{it} \cdot LR_{M,t-1} \\ z_{it} \cdot LR_{i,t-1} \\ z_{Mt} \cdot LR_{M,t-1} \end{bmatrix} i = 1,2,3. \tag{15}$$

for a total of 7 restrictions.

Second, since we use weekly data (see below), there may be serial correlation in the portfolio returns, for example because of liquidity problems, that is not captured by the CAPM model. The MEAN test implicitly tests the serial correlation properties of the returns, but we also provide a more explicit test by putting

$$V_t = \begin{bmatrix} z_{it} \cdot r_{M,t-1} \\ z_{it} \cdot r_{i,t-1} \\ z_{Mt} \cdot r_{M,t-1} \end{bmatrix} i = 1,2,3. \tag{16}$$

The $CAPM_2$ test has 7 restrictions and also tests whether past market portfolio returns predict future portfolio residuals, which may be the case if liquidity problems prevent information from being incorporated quickly into the prices of smaller stocks.

Third, previous research (see e.g. Harvey (1991), Bekaert and Harvey (1995) and DeSantis and Gerard (1996)) has uncovered time variation in the prices of risk for a large number of equity markets across the world. It is likely that the price of risk varies with the business cycle (see Campbell and Cochrane 1995). Therefore, we also consider a more general model with a time-varying price of risk. In particular, we let

$$Y_t^A = \left[Y_1 I_{(r^f_{t-1,t} > MA(10))} + Y_2 I_{(r^f_{t-1,t} \leq MA(10))} \right] / \left(1 + LR_{M,t}\right) \tag{17}$$

where $MA(10)$ represents a 10 week moving average of past interest rates and I is the indicator function. Hence, the price of risk can take on two values depending on whether interest rates are high or low relative to a moving average of past interest rates. The link between interest rates and business cycles is well-known. This model is an estimable, one parameter extension of our general model that avoids the large swings in the price of risk implied by standard empirical models of time-varying prices of risk (see the references above). Our CAPM_3 test is a likelihood ratio test of the restriction $Y_1 = Y_2$.

2.4.3 Interest Rate Effects

As stressed by Christie (1982), and confirmed by a number of empirical studies, interest rates are good predictors of stock market volatility. Interest rate changes also affect the market value of debt and hence leverage ratios. Since we use book values of debt in the empirical work below, the measurement error in leverage ratios may be correlated with interest rates.

We examine remaining interest rate effects in both conditional variances and co-variances. INT_1 sets

$$V_t = \left[q_{i,t} \cdot r^f_{t-1,t}\right] \quad i = M, 1, 2, 3, \tag{18}$$

and INT_2 lets

$$V_t = \left[W_{i,t} \cdot r^f_{t-1,t}\right] \quad i = 1, 2, 3, \tag{19}$$

Finally, if debt is not riskless, the conditional mean for equity returns depends on the risk free rate through the expected excess return on debt. Hence for INT_3, we set

$$V_t = \left[z_{i,t} \cdot r^f_{t-1,t}\right] \quad i = M, 1, 2, 3. \tag{20}$$

3. Empirical Results

3.1 The Nikkei 225 Data

Our data consists of daily observations on the (dividend-adjusted) prices and market capitalization of the firms in the Nikkei 225 index. In addition, we have biannual data on their book value of debt. The sample period is from January 1, 1985 to June 20, 1994. Stocks that are not in the Nikkei 225 index over the whole period or do not have debt data are discarded. There are 172 stocks left in the sample. We construct three portfolios of 5 stocks each, representing a low leverage, medium leverage and high leverage portfolio. To do so, daily leverage ratios are calculated, with missing debt data set equal to the last available data point. Then we rank all firms according to their average leverage ratios. The leverage portfolios consist of five stocks with the lowest, the medium or the highest leverage ratios, respectively, excluding commercial banks[10]. The portfolio leverage ratios are then calculated as the total debt over the total capitalization of the portfolio. For the market leverage ratio, we use the ratio of total debt over total capitalization of the 172 stocks left in the sample. Finally we extract weekly observations on leverage and stock returns from the daily data.

The leverage ratio data are measured with error because the debt value is a book instead of market value and because it is only updated every six months. Moreover, the substantial time-variation observed in the capital structure of a firm over a 10-year period, may make a classification based on leverage difficult. Nevertheless, Table 2 shows that our portfolios have very distinct leverage ratios over the full sample period. In particular, the leverage ranking is preserved not only on average but at every point in time. Their return characteristics do not appear significantly different.

For the short term interest rate, we use the 1-month Gensaki rate, which is the yield on bond repurchase contracts[11]. As noted in Dickson, Fuchida and Nishizawa (1990), the Gensaki market was the first open market short-term investment with rates determined freely by supply and demand of funds.

3.2 Estimation and Specification Tests

To estimate the model in equations (5) -(11), we assume that the innovations are conditionally normal. We obtain quasi-maximum likelihood estimates of the parameters with White (1980) standard errors, unless mentioned otherwise. To improve the conditioning of the system, all the leverage ratios are scaled by a factor of 0.01. The price of risk is estimated to be 2.842 with a standard error of 4.071. This is the only parameter that is significantly affected by the leverage adjustment to the price of risk. That is, the model without the adjustment and hence a constant price of risk at the equity level yields very similar volatility dynamics[12]. Importantly, the price of risk is positive so that we can proceed with the analysis of volatility feedback effects.

Before we do so, we want to ensure that the model is well specified. The specification tests discussed in Section 2.4 are reported in Table 3. The MEAN, VAR and COV statistics reveal little

[10] See the Appendix for the list of all stocks included in the leverage portfolios. Portfolios are constructed analogous to the construction of the Nikkei 225 index, that is, the total value of a portfolio is the sum of the value of individual stocks with dividends reinvested.

[11] We divide the annualized rate by 5200 to express it as a weekly yield. Implicitly, we assume a flat term structure of interest rate at the very short end of the maturity spectrum.

[12] Therefore we will not report results from this constant price of risk model, which are available upon request from the authors.

evidence against the model. Only the MEAN statistic rejects at the 5% level for the market portfolio. Given that these tests are likely to over-reject at the asymptotic critical value (see Bekaert and Harvey (1997)), there is no strong evidence against the model. There do not appear to be interest rate effects in the variance, covariance and mean expectations that we fail to capture. However, there is some evidence against the CAPM model. Leverage ratios may have some remaining predictive power but the test does not reject at the 1% level (CAPM_1). The constant price of risk model is strongly rejected by a likelihood ratio test (CAPM_3). Despite this evidence, we continue to work with the constant price of risk model for three reasons. First, the estimates of the prices of risk are economically plausible as to their relative magnitude – the price of risk is larger when the interest rate is below the moving average – but implausible in their absolute magnitude. Y_1 is actually negative at -4.51, whereas Y_2 equals 8.11. Second, the volatility dynamics of the constant and time varying price of risk models are fairly similar. Finally, on the root-mean-squared error criterion we employ later (see section 3.5), the constant price of risk model dominates.

3.3 Volatility Persistence, Volatility Feedback and Leverage Effects

3.3.1 Likelihood Ratio Tests

The simultaneous presence of leverage ratios, asymmetric shocks and volatility persistence makes our model more general than previous volatility specifications. In Table 4, we present a number of likelihood ratio tests to determine the potential validity of more restrictive models.

First, the $B = C = D = 0$ restrictions basically represent the GARCH structure, which is typically ignored in the literature focusing on individual firms and leverage effects. Clearly, leverage variables alone cannot account for the volatility behavior of the Japanese stock returns.

Second, since both the asymmetric shocks (η) and the leverage ratios give rise to asymmetric volatility, it may be superfluous to have both. For example, the η terms may indirectly capture the leverage effect in addition to volatility feedback effects. The overwhelming rejection of $G = 0, D = 0$ and the joint hypothesis $G = D = 0$ show that this is not the case. In part, the presence of leverage ratios may simply enable the BEKK model to capture strong asymmetry (see footnote 4). We investigate whether the model generates strong asymmetry below.

Third, as discussed in section 2, we test a model in which leverage ratios unambiguously capture leverage effects (G diagonal) and the η variables unambiguously capture volatility feedback effects

(D all zero except the first column). The strong rejection of this model indicates that interaction effects are important, which makes it hard to disentangle volatility feedback from leverage effects.

3.3.2 Volatility Dynamics

The dynamics of conditional variances are driven by a number of variables in our model. Market variance, for example, is related to the past conditional market variance, the squared market return shock, the squared asymmetric shock and the leverage ratio of the market portfolio. By assumption, it is not affected by the analogous variables of the individual portfolios. However, individual portfolio variances are affected by their own variables and those of the market portfolio. Figure 2 plots the estimated conditional variances for the market portfolio and the three leverage sorted portfolios.

Table 5 shows the estimated VEC form coefficients of the variance equations with standard errors in parentheses. The parameter estimates in Table 5 imply that conditional volatility is quite persistent both at the market level and at the portfolio level. The coefficient on lagged volatility is always significant and between 0.3701 and 0.8888. At the market level, the asymmetry of volatility response to return shocks is significant and pronounced. The coefficient on the squared return shock is 0.0647 and insignificant while the coefficient on the squared asymmetric shock term is 0.2089 and significant. Recall that the asymmetric shock term is defined to be the negative component of the return shock. Thus, negative shocks have a large impact on conditional volatility, whereas positive shocks have negligible effect. In fact, one disadvantage of the BEKK model is that it does not accommodate the strong form of asymmetric volatility where positive return shocks decrease conditional volatility (see equation 1 and the associated footnote). Even so, the model yields pronounced asymmetry.

The asymmetry of the volatility response to shocks is best illustrated by the shock impact curves in Figures 4a-4d and shock impact surfaces in Figures 5a-5d. These figures incorporate the effect of the leverage variables. Table 5 reveals that most leverage variables fail to significantly affect conditional variances. For the low leverage portfolio, both its own and the leverage variable enter significantly whereas for the high leverage portfolio only its own leverage variable is statistically significant, but the effect of market leverage seems quite large. Nevertheless, the economic effects of these variables are sometimes large, as we will discuss below. Figure 4a shows the impact of market return shocks on the market conditional variance. For a return shock of the same magnitude, a negative shock clearly increases the conditional variance much more than a positive shock, hence the volatility asymmetry. Figures 4b-4d focus on the leverage portfolios. The high leverage portfolio exhibits distinct and strong asymmetry both with respect to market shocks and portfolio shocks. The latter is weaker and entirely driven by the leverage variables. Moreover, once interaction effects are accounted for (Figure 5b), it disappears. The medium leverage portfolio shows a similar picture (see Figures 4c and 5c) with the exception that the leverage variables have no detectable effects on the volatility response. The dynamics for the low leverage portfolio (Figures 4d and 5d) are quite different. The low leverage portfolio exhibits a small asymmetry effect caused by its own portfolio shocks. Market shocks have a symmetric impact on the conditional volatility of the low leverage portfolio.

Although the leverage ratios are statistically significant overall in the model, changes in leverage directly generate only small changes in conditional volatility. There are a number of reasons why we may underestimate the importance of the leverage variables. First, the shock terms ϵ and η are correlated with the leverage ratio. When there is a negative shock, coefficients on the shock term imply that conditional variance should increase, which is also implied by the increased leverage ratio. It is possible that some of the explanatory power of the leverage ratio has been taken away by the shock terms in the volatility equation. However, the estimated correlation coefficients between leverage ratios and the shock terms fitted from the estimated model are all smaller than 0.11 in absolute value. (The correlation coefficients are presented in the Appendix.) Second, the measurement error associated with the leverage variable may induce downward bias in the estimated coefficients. As illustrated above we use book value of debt rather than the market value, which is updated every six months. Finally, leverage ratios may be indirectly important through the covariance equations (see Section 3.4).

To conclude, our results indicate that the high and medium leverage portfolios exhibit pronounced asymmetry caused by market shocks. For the low leverage portfolio, the asymmetry seems economically less significant. For the volatility feedback story to explain the asymmetry in the high and medium leverage portfolios, negative shocks at the market level must lead to an increase of conditional covariances between the market and these portfolios. We examine this issue in the next section.

3.4 Conditional Covariances

At the portfolio level, the conditional covariance plays an important role in determining the expected excess return and volatility feedback according to the time varying risk premium theory. How do return shocks and leverage ratios affect the conditional covariance? Table 6 summarizes the estimated coefficients and their standard errors (in parentheses). The conditional covariances between the market portfolio and the leverage portfolios are very persistent and show quite a bit of time variation, suggesting that required excess returns for these portfolios change substantially over time. Figure 6 plots the estimated conditional covariances for the three portfolios. Overall, the covariances for the three leverage portfolios track each other over the whole sample period, and the portfolio with higher leverage tends to have a higher conditional covariance with the market.

It is interesting to note the existence of pronounced covariance asymmetry in the high and medium leverage portfolios. The asymmetry is caused by market return shocks rather than portfolio specific shocks. When there is a one percentage point negative return shock to the market portfolio, the impact on the conditional covariance between the high leverage portfolio and the market is significant and larger than $0.1775 * 10^{-4}$, while a one unit positive shock increases covariance only by $0.0168 * 10^{-4}$and it is statistically insignificant. For the medium leverage portfolio, the corresponding values are $0.2991 * 10^{-4}$ vs. $-0.0388 * 10^{-4}$. The cross product terms $\epsilon_{i,t-1}\epsilon_{M,t-1}$ and $\eta_{i,t-1}\eta_{M,t-1}$ have much smaller coefficients for these two portfolios. For the low leverage portfolio, the market level shocks have no significant impact on the conditional covariance and there is little evidence of covariance asymmetry.

Figure 7 plots the covariance responses to market return shocks assuming portfolio shocks are zero. The results confirm our analysis in Section 2 about firm level volatility feedback. Bad news at the market level increases the conditional covariances with the market of the high and medium leverage portfolios substantially, inducing a volatility feedback effect. The low leverage portfolio displays a smaller asymmetric effect than the market, the high and medium leverage portfolios because its covariance with the market does not increase very much in response to a negative market return shock. Figure 7 ignores the effect of leverage variables and interaction effects. This is rectified in the impact surfaces of Figures 8a-8c. The high and medium leverage portfolios continue to show pronounced asymmetry with respect to market shocks. Part of this effect could come from a leverage effect. As equation (3) shows, positive market shocks reduce market leverage and hence automatically reduce the covariance of the stock return with the market portfolio stock return, even though the asset covariance need not change. Such strong asymmetry is only observed for negative portfolios shocks however. These results confirm that the volatility asymmetry documented in Section 3.3 for the high and medium leverage portfolios is closely related to the asymmetric response of the covariance with respect to market shocks. The magnitude of the effects is enhanced by the presence of the leverage variables – at least for negative portfolio shocks. Overall, volatility feedback seems to be the dominant factor behind asymmetry.

3.5 Conditional Betas

In Figure 9, we graph the conditional betas implied by the model for all three leverage portfolios. The betas vary substantially over time and a higher leverage level is associated with a higher beta. At times of major market fluctuations, as marked by the vertical lines, the betas for all portfolios approach 1 dramatically. This makes intuitive sense. Such major market movements typically stem from macro economic or political events rather than from firm or industry specific news. All stocks then move with the market portfolio and the riskiness of all portfolios approaches that of the market portfolio.

Although some authors have found a "leverage effect" in conditional betas, Braun, Nelson and Sunier(1995) find no evidence that betas rise (fall) in response to bad (good) news at the industry level. As equation (4) indicates, this is a priori not so surprising. If market leverage changes simultaneously and shocks are not purely idiosyncratic, the change in market leverage may mitigate the leverage effect of the portfolio shock. The relation between market shocks and the market beta is not very transparent in this model, since shocks affect both the conditional variance and covariance in a similar way. Nevertheless, if the leverage effect is important, we ought to unambiguously see rises in betas when market shocks are positive and portfolio shocks are negative. Figures 10a-10c graph news impact surfaces for the betas of the three leverage portfolios. The graph for the high and medium leverage portfolios show the opposite effect. Betas sharply drop in response to highly positive market and negative portfolio shocks. Even for small market shocks, beta is higher when positive portfolio shocks hit than when comparable negative portfolio shocks occur. These numbers have to be interpreted with caution, however. As Table 7 indicates, the high and medium leverage portfolios have average betas somewhat higher than one. The simultaneous occurrence of a large positive market shock and negative portfolio shock is very unlikely. Moreover, the drop in beta when large market shocks hit is consistent with the convergence to 1 of all betas in such circumstances (see Figure 9).

If this is the dominant force behind the beta movements, we should expect the low leverage portfolio to exhibit a reverse effect, since its beta is lower than 1 on average (See Table 7). That is, beta should increase for large market shocks. Figure 10c shows this is indeed the case, but only for positive market shocks. For negative market shocks, we observe beta asymmetry of the form predicted by a standard leverage story. Beta decrease in response to positive portfolio shocks and vice versa. A similar effect is visible for the medium leverage portfolio. The fact that the low leverage beta responds positively to positive market shocks may also be caused by the leverage effect of equation (4).

We conduct two more exercises. Ghysels (1997) recently reports that one class of time-varying beta models fail to capture beta risk dynamics well and are dramatically outperformed by a constant beta model according to the (in sample) root mean square error (RMSE) criterion. In the class of models we consider, betas are a function of a number of information variables (see for example, Ferson and Harvey (1993)), which induce excess time-variation in the conditional betas. As Table 7 shows, the standard deviation of the conditional betas implied by our model is at most 0.20 (for the medium leverage portfolio), although Figure 9 reveals occasional erratic high frequency movements in the conditional betas of the various portfolios. Panel A of Table 8 shows the in sample RMSE results of our model relative to a number of standard and simpler models. The unconditional beta model uses the sample beta whereas the rolling beta model uses a rolling sample of 260 weekly observations in estimating beta. Note that our model and the time-varying price of risk model need to predict both market risk premium and beta. Thus, for the unconditional beta model and the rolling beta model, we use the predicted value of market risk premium from our model to make the comparison meaningful. Surprisingly, the rolling and constant beta models have marginally lower RMSE's for all portfolios. However, when these models use the average market excess return to proxy for the market risk premium, instead of the risk premium implied by our model, our model marginally outperforms. Although the performance of our model seems relatively better than that of the models examined in Ghysels (1997), it is surprising how well the rolling and constant beta models do. It should be noted that the results are not very robust and sensitive to the sample selection. For example, our model performs relatively better when the first 260 observations are included. This may reflect parameter instability but still is surprising that the time-varying price of risk model (which allows one parameter to change over time) does not perform substantially better than the constant price of risk model. There are a number of alternative interpretations. First, our model may outperform the other models according to economically more relevant criteria than the RMSE, which is just an "average" pricing error. Second, our model may mis-specify the beta dynamics. Kroner and Ng (1995), for example, illustrate the general difficulty multivariate GARCH models have in modeling covariance dynamics. Nevertheless, our model has passed an extensive array of specification tests (see Section 3.2), which includes tests on the covariance dynamics. It is definitely possible that the true betas display even smoother temporal behavior than implied by our model. Third, our model may be an adequate model to describe beta dynamics but sampling error causes the model to "misprice" on average relative to simpler models, which require very few parameters to estimate. Although these questions are beyond the scope of the current paper, they certainly deserve further scrutiny.

Finally, we ran the Ball and Kothari regressions. We report results for k_J =13, 26 and 52 for the three portfolios in Panel B of Table 8. The coefficient is only significantly and consistently negative for the low leverage portfolio. This is not surprising. The low leverage portfolio has a relatively small beta (see Table 7), so that idiosyncratic shocks may dominate the variation in its return. As a consequence, the "loser" effect may actually occur and negative shocks may actually increase beta. The betas of the other portfolios may be too close to one to see significant effects.

4. Is there a size effect in asymmetric volatility?

Cheung and Ng (1992) show that volatility asymmetry is much stronger for small U.S. stocks. To examine whether our results are robust and whether a similar effect exists for the Japanese stocks, we apply our model to size-sorted portfolios. More precisely, we divide our universe of Japanese stocks into tritiles based on average market capitalization over the sample period. Within the smallest and the largest tritile, we select three leverage portfolios of 5 stocks. The stocks are chosen so as to match the average leverage ratio of the portfolios in the main estimation as closely as possible. The fact that such modeling was successful indicates that leverage ratios and size are not strongly correlated.

The results for the impact coefficients estimated from small and large firm portfolios are presented in Table 9 (for the variances) and Table 10 (for the covariances). First, we do not generally confirm Cheung and Ng's results for the sample. It is not true that small size firms show more pronounced asymmetries than large size firms. For example, asymmetries for the high leverage portfolio are stronger for the small firm/portfolio at the portfolio shock level but not at the market shock level. Only the small size medium leverage portfolio unambiguously shows stronger volatility asymmetry than its large size counterpart.

Second, it is hard to draw firm conclusions on the relative importance of market and portfolio shock induced asymmetries, since the coefficients on the leverage variables and asymmetric shocks are not perfectly correlated. Clearly the volatility dynamics of the high leverage/large firm portfolios are dominated by market shocks whereas those of the low leverage/small firm portfolios are dominated by portfolios shocks. Covariance asymmetries seem to be most pronounced for the low leverage/small firm portfolio[13].

All in all, neither size nor leverage seems to differentiate the dynamic behavior of volatility and risk across portfolios very well. Looking back at Table 7, which lists the capitalization and betas of the various returns in our different estimations, an interesting conclusion emerges. What may be more important than leverage or size is simply the beta of the firm. For example, the low leverage portfolio in our original estimation exhibits very distinct volatility dynamics from the high and medium leverage portfolios. In particular, its volatility dynamics are primarily driven by portfolio shocks and the leverage effect seems to be more important than the volatility feedback effect. If one looks at our size sorted portfolios, it is also the case that the low-beta firms (e.g., the large size/low leverage and small size/high leverage portfolios) show such volatility behavior. For the high beta firms on the other hand, market shocks induce pronounced covariance and volatility asymmetry.

5. Conclusions

In this paper, we investigate the leverage effect and the time varying risk premium explanations of the asymmetric volatility phenomenon at both the market and firm level. Our results rely on a

[13] Note the perfect rank correlation between the effect of $\eta_{it}\eta_{Mt}$ term on the conditional covariance and the importance of asymmetry through the portfolio shocks in the conditional variance. Part of this correlation in parameter estimates is accounted for by the non-linear restrictions on the parameters imposed by the BEKK framework, but these results stress again the importance of the interaction between leverage and volatility feedback effects. Covariance asymmetry, which at the firm level causes volatility feedback effect, is magnified by changes in firm and market leverage (see equation (3)). The latter effect seems to be captured by $\eta_{it}\eta_{Mt}$ term in the covariance equation and its effect on volatility by the η_{it} variables.

conditional CAPM model using a multivariate GARCH-in-mean parameterization applied to four portfolios from the Nikkei 225 stocks. For the market portfolio, a high leverage and a medium leverage portfolio, a pronounced asymmetry effect mainly arises from market shocks. For the low leverage portfolio, the asymmetry is still statistically significant, but its magnitude is smaller and arises from firm-specific shocks.

The leverage variables are statistically important in the conditional variance equations, especially for the low leverage portfolio. However, their effect on volatility seem small compared to the asymmetry generated through the shocks in the GARCH specification, although they sometimes generate strong asymmetry. The main mechanism behind the asymmetry for the high and the medium leverage portfolios is covariance asymmetry. Negative shocks increase conditional covariances substantially, whereas positive shocks have a mixed impact on conditional covariances. This phenomenon can partially be attributed to a pure leverage effect. The conditional betas do not behave as predicted by the leverage story, except for the low leverage portfolio. Taken together our results suggest that "the leverage effect" may be a misnomer.

Although our results seem consistent with the existence of time-varying risk premiums and volatility feedback, there may be other factors driving the results. For example, it is unlikely that standard general equilibrium models with an expected-utility maximizing representative agent would generate time-variation in equity risk premiums that is as large as shown in Figure 3. In the future, we hope to explore whether models where agents exhibit loss aversion can generate asymmetric volatility effects in equilibrium. Another item left for future research is to examine whether our results hold up for U.S. data. In particular, we would like to see whether the difference in the sources of asymmetry for low and high leverage firms is country-specific.

References

Amin, Kaushik and Victor Ng, 1993, "ARCH Process and Option Valuation," Working Paper, School of Business Administration, University of Michigan.

Backus, David and Allan Gregory, 1993, "Theoretical relations between risk premiums and conditional variance," *Journal of Business & Economic Statistics,* 11, pp. 177-185.

Ball, R. and S. P. Kothari, 1989, "Nonstationary Expected Returns: Implications for Tests of Market Efficiency and Serial Correlation in Returns," *Journal of Financial Economics*, 25, 51-74.

Bhandari, Laxmi Chand, 1988, "Debt/Equity Ratio and Expected Common Stock Returns: Empirical Evidence," *Journal of Finance*, 43, pp. 507-528.

Bekaert, Geert and Campbell R. Harvey, 1995, "Time-Varying World Market Integration," *Journal of Finance*, 50, pp. 403-444.

Bekaert, Geert and Campbell R. Harvey, 1997, "Emerging Equity Market Volatility," *Journal of Financial Economics,* 43, 29-77.

Black, Fischer, 1976, "Studies of Stock Price Volatility Changes," *Proceedings of the 1976 Meetings of the American Statistical Association, Business and Economical Statistics Section*, pp. 177-181.

Bollerslev, Tim, 1990, "Modeling the Coherence in Short Run Nominal Exchange Rates: A Multivariate Generalized ARCH Approach," *Review of Economics and Statistics*, 72, pp. 498-505.

Bollerslev, Tim, Robert Engle and J. Wooldridge, 1988, "A Capital Asset Pricing Model with Time Varying Covariances," *Journal of Political Economy*, 96, pp. 116-131.

Bollerslev, Tim, Ray Y. Chou and Kenneth F. Kroner, 1992, "ARCH Modeling in Finance," *Journal of Econometrics*, 52, pp. 5-59.

Braun, Phillip A., Daniel B. Nelson and Alain M. Sunier, 1995, "Good News, Bad News, Volatility, and Betas," *Journal of Finance*, 50, pp. 1575-1603.

Campbell, John Y., 1993, "International Asset Pricing without Consumption Data," *American Economic Review*, 83, pp. 487-512.

Campbell, John Y. and John H. Cochrane, 1995, "By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior," Working Paper No. 4995, NBER.

Campbell, John Y. and Ludger Hentschel, 1992, "No News is Good News: An Asymmetric Model of Changing Volatility in Stock Returns," *Journal of Financial Economics*, 31, pp. 281-318.

Chan, K. C, 1988, "On the Contrarian Investment Strategy," *Journal of Business*, 61, 147-163.

Cheung, Yin-Wong and Lilian Ng, 1992, "Stock Price Dynamics and Firm Size: An Empirical Investigation," *Journal of Finance*, 47, pp. 1985-1997.

Christie, Andrew A., 1982, "The Stochastic Behavior of Common Stock Variances – Value, Leverage and Interest Rate Effects," *Journal of Financial Economics*, 10, pp. 407-432.

Cox, John C. and Stephen A. Ross, 1976, "The Valuation of Options for Alternative Stochastic Processes," *Journal of Financial Economics*, 3, pp. 145-166.

Das, Sanjiv and Raman Uppal, 1996, "State Varying Correlations: A Theoretical and Empirical Analysis," Working Paper, University of British Columbia.

DeSantis, Georgio and Bruno Gerard, 1996, "International Asset Pricing and Portfolio Diversification with Time-Varying Risk," Working Paper, University of Southern California.

Dickson, Jeffrey L., Hiroaki Fuchida and Yutaka Nishizawa, 1990, "The Gensaki Market," in *The Japanese Bond Markets*, Frank Fabozzi, editor, Probus Publishing Company.

Duan, Jin-Chuan, 1995, "Fitting and "Smile Family" – A GARCH Approach," Working Paper, McGill University.

Duffee, Gregory R., 1995, "Stock Returns and Volatility: A Firm Level Analysis," *Journal of Financial Economics*, 37, pp. 399-420.

Engel, Charles, Jeffrey A. Frankel, Kenneth A. Froot and Anthony P. Rodrigues, 1995, "Tests of Conditional Mean-Variance Efficiency of the U.S. Stock Market," *Journal of Empirical Finance*, 2, pp. 3-18.

Engle, Robert F. and Kenneth Kroner, 1995, "Multivariate Simultaneous Generalized ARCH," *Econometric Theory*, 11, pp. 122-150.

Engle, Robert F., David M. Lilien and Russell P. Robbins, 1987, "Estimating Time Varying Risk Premia in the Term Structure: The ARCH-M Model," *Econometrica*, 55, pp. 391-407.

Engle, Robert F. and Victor K Ng, 1993, "Measuring and Testing the Impact of News on Volatility," *Journal of Finance*, 48, pp. 1749-1778.

Engle, Robert F. and Victor K Ng and M. Rothschild, 1990, "Asset Pricing with a Factor ARCH

Covariance Structure: Empirical Estimates for Treasury Bills," *Journal of Econometrics*, 45, pp. 213-238.

Ferson, Wayne E. and Campbell R. Harvey, 1993, "The Risk and Predictability of International Equity Returns," *Review of Financial Studies*, 6, pp. 527-566.

French, Kenneth R., G. William Schwert and Robert Stambaugh, 1987, "Expected Stock Returns and Volatility," *Journal of Financial Economics*, 19, pp. 3-29.

Ghysels, Eric, 1997, "On Stable Factor Structures in the Pricing of Risk: Do Time-varying Betas Help or Hurt," *Journal of Finance*, forthcoming.

Glosten, Lawrence R., Ravi Jagannathan and David E. Runkle, 1993, "On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks," *Journal of Finance*, 48, pp. 1779-1801.

Hamao, Yasushi and Ronald W. Masulis and Victor Ng, 1990 "Correlations in Price Changes and Volatility across International Stock Markets," *Review of Financial Studies*, 3, pp. 281-307.

Harvey, Campell R.,1991, "The World Price of Covariance Risk," *Journal of Finance*, 46, pp. 111-157.

Hentschel, Ludger, 1995, "All in the family : Nesting symmetric and asymmetric GARCH models," *Journal of Financial Economics*, 39, pp. 71-104.

Hull, John and Alan White, 1987, "The Pricing of Options on Assets with Stochastic Volatilities," *Journal of Finance*, 42, pp. 281-300.

Jagannathan, Ravi, Keiichi Kubota and Hitoshi Takehara, 1996, "Income Risk and the Cross-Section of Average Returns on Stocks: Some Insights from the Japanese Stock Market," Working Paper, University of Minnesota.

Jagannathan, Ravi and Zhenyu Wang, 1996, "The Conditional CAPM and the Cross-Section of Expected Returns," *Journal of Finance*, 51, pp. 3-53.

Koutmos, Gregory and Geoffrey Booth, 1995, "Asymmetric Volatility Transmission in International Stock Markets," *Journal of International Money and Finance*, 14, pp. 747-762.

Koutmos, Gregory and Reza Saidi, 1995, "The Leverage Effect in Individual Stocks and the Debt to Equity Ratio," *Journal of Business Finance and Accounting*, 22, pp. 1063-1075.

Kroner, Kenneth F. and Victor K. Ng, 1995, "Modeling the Time Varying Comovement of Asset

Returns," Working Paper, Advanced Strategy Research Group, Wells Fargo Nikko Investment Advisors.

Longin, Francois and Bruno Solnik, 1995, "Is the Correlation in International Equity Returns Constant: 1960-1990?," *Journal of International Money and Finance*, 14, pp. 3-26.

Merton, Robert C., 1973, "The Theory of Rational Option Pricing," *Bell Journal of Economics and Management Science*, 4, pp. 141-183.

Modigliani, Franco and Merton Miller, 1958, "The Cost of Capital, Corporate Finance, and the Theory of Investment," *American Economic Review*, 48, pp. 261-297.

Nelson, Daniel B., 1991, "Conditional Heteroskedasticity in Asset Returns: A New Approach," *Econometrica*, 59, pp. 347-370.

Ng, Angela, 1996, "Volatility Spillover Effects from Japan and the U.S. to the Pacific-Basin," Working Paper, Department of Economics, Stanford University.

Pagan, Adrian R. and G. William Schwert, 1990, "Alternative Models for Conditional Stock Volatility," *Journal of Econometrics*, 45, pp. 267-290.

Pindyck, Robert S., 1984, "Risk, Inflation, and the Stock Market," *American Economic Review*, 74, pp. 334-351.

Schwert, G. William, 1989, "Why Does Stock Market Volatility Change Over Time?," *Journal of Finance*, 44, pp. 1115-1153.

Schwert, G. William, 1990, "Stock Volatility and the Crash of '87," *Review of Financial Studies*, 3, pp. 77-102.

Sharpe, William, 1964, "Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk," *Journal of Finance*, 19, pp. 425-442.

Solnik, Bruno, 1993, "The Performance of International Asset Allocation Strategies Using Conditioning Information," *Journal of Empirical Finance*, 1, pp. 33-55.

Turner, Christopher M., Richard Startz and Charles R. Nelson, 1989, "A Markov Model of Heteroskedasticity, Risk, and Learning in the Stock Market," *Journal of Financial Economics*, 25, pp. 3-22.

White, Halbert, 1980, "A Heteroskedasticity Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity," *Econometrica*, 48, pp. 817-838.

Wu, Guojun, 1997, "The Determinants of Volatility Asymmetry: Evidence from Option Prices," Manuscript, Graduate School of Business, Stanford University.

Table 1: Summary of Selected Empirical Studies on Asymmetric Volatility

Study	Volatility Measure	Presence of Asymmetry	Explanation
Black (1976)	Gross Volatility	Stocks, Portfolios	Leverage Hypothesis
Christie (1982)	Gross Volatility	Stocks, Portfolios	Leverage Hypothesis
French, Schwert and Stambaugh (1987)	Conditional Volatility	Index	Time Varying Risk Premium Theory
Schwert (1990)	Conditional Volatility	Index	Leverage Hypothesis
Nelson (1991)	Conditional Volatility	Index	Unspecified
Campbell and Hentschel (1992)	Conditional Volatility	Index	Time Varying Risk Premium Theory
Cheung and Ng (1992)	Conditional Volatility	Stocks	Unspecified
Engle and Ng (1993)	Conditional Volatility	Index (Japan Topix)	Unspecified
Glosten, Jagannathan and Runkle (1993)	Conditional Volatility	Index	Unspecified
Braun, Nelson and Sunier (1995)	Conditional Volatility	Index and stocks	Unspecified
Duffee (1995)	Gross Volatility	Stocks	Leverage Hypothesis
Bekaert and Harvey (1997)	Conditional Volatility	Index (Emerging Markets)	Unspecified

NOTES: This table lists a sample of studies on the relationship between returns and conditional volatility. Conditional volatility studies typically use GARCH models to measure volatility; gross volatility typically refers to the standard deviation of daily returns computed over the course of a month. The "unspecified" label in the Explanation column means that asymmetry was modeled but the researchers did not specify the exact cause of asymmetry.

Table 2: Summary Information of the Leverage Portfolios (weekly)

		market	high lev	med. lev	low lev
Returns of Portfolios	maximum	10.269	13.947	12.358	22.213
	minimum	-12.790	-13.956	-21.849	-15.378
	mean	0.126	0.165	0.108	0.209
	std deviation	2.671	3.843	3.831	3.426
	AC(1)	0.028	-0.023	0.015	-0.061
	AC(2)	0.050	0.030	0.023	0.015
	AC(3)	0.090	0.051	0.136	0.006
	AC(4)	-0.021	0.003	-0.030	-0.070
	AC(5)	0.008	0.053	-0.033	0.012
leverage ratios of Portfolios		market	high lev	med. lev	low lev
	maximum	2.430	10.844	1.402	0.362
	minimum	0.753	2.971	0.393	0.137
	mean	1.354	5.796	0.835	0.210
	std deviation	0.445	1.895	0.263	0.054

NOTES: This table provides summary information about the market portfolio and the three basic leverage portfolios that we study in this paper. The three leverage portfolios are constructed with five stocks each which have the highest, the medium and the lowest average leverage ratios over the sample period, excluding commercial banks. The base series for the study is the weekly holding period returns for the four portfolios.

Table 3: Tests of the Model Specification

Test Statistics	MEAN	VAR	COV	$CAPM_1$	$CAPM_2$	$CAPM_3$	INT_1	INT_2	INT_3
General				15.709 (0.028)	6.256 (0.510)	10.09 (0.0015)	0.295 (0.990)	1.626 (0.653)	0.501 (0.973)
Market Portfolio	9.907 (0.042)	3.635 (0.458)							
High Leverage	2.735 (0.603)	5.786 (0.216)	3.344 (0.502)						
Medium Leverage	1.492 (0.828)	1.649 (0.800)	2.913 (0.573)						
Low Leverage	1.109 (0.893)	1.610 (0.807)	8.697 (0.069)						

NOTES: This table provides the results for the specification tests. The model is the one where price of risk with respect to *firm* (as opposed to *stock*) is assumed to be constant. The first row is the value of the statistic and the second row contains the p-value (in parentheses). MEAN tests whether the means and three autocorrelations of the standardized residuals are zero; VAR tests whether the means of the squared standardized residuals are 1 and three autocorrelations of the squared standardized residuals are zero. The MEAN and VAR tests have asymptotic χ^2 distribution with 4 degrees of freedom. COV provides an analogous test for the cross residuals scaled by the conditional covariance and is asymptotically distributed as a χ^2 (3). The first two CAPM statistics test the orthogonality of scaled residuals to respectively past leverage ratios and past returns ($CAPM_1$ and $CAPM_2$ are χ^2 (7)). $CAPM_3$ is a likelihood ratio test of the null of a constant price of risk and is a χ^2 (1). Finally, the INT-tests focus on the orthogonality of standardized variances, covariances and residuals to past interest rates. All tests are χ^2 (4).

Table 4: Likelihood Tests for Various Models

Null Hypothesis	Test Statistic	Degrees of Freedom	P-Value
$G=0$	70.41	7	1.2208e-012
$D=0$	122.48	7	0
$D=G=0$	126.20	14	0
$B=C=D=0$	269.18	21	0
$D=D^R$	41.93	3	4.1517e-009
$G=G^R$	65.50	3	3.9191e-014
$D=D^R$, $G=G^R$	71.73	6	1.8052e-013

NOTES: This table presents the likelihood ratio tests of various restrictions on the model. B, C, D and G are parameter matrices in the BEKK covariance matrix process (see equation 10) for the lagged covariances, return shocks, asymmetric shocks and leverage ratios, respectively. These tests check for the significance of the presence of these variables. The estimation for $D=D^R$ restricted model did not converge. We use the largest available likelihood value for the test, thus this particular result must be viewed with caution.

Table 5: Impact of Variables on Conditional Variances

Equation	$\sigma^2_{M,t-1}$	$\sigma^2_{i,t-1}$	$\varepsilon^2_{M,t-1}$	$\varepsilon^2_{i,t-1}$	$\eta^2_{M,t-1}$	$\eta^2_{i,t-1}$	$10^{-2}\,LR^2_{M,t-1}$	$10^{-2}\,LR^2_{i,t-1}$
Market	0.7357		0.0647		0.2089		0.0000	
	(0.0592)		(0.0414)		(0.0783)		(0.0000)	
High	0.0784	0.3701	0.0043	0.0363	0.1509	0.0007	0.5278	0.0272
	(0.1044)	(0.2035)	(0.0191)	(0.0351)	(0.1518)	(0.0072)	(0.2924)	(0.0155)
Medium	0.0037	0.8007	0.0233	0.1018	0.4281	0.0007	0.0003	0.0021
	(0.0073)	(0.0626)	(0.0353)	(0.0362)	(0.1891)	(0.0065)	(0.0011)	(0.0054)
Low	0.0116	0.8888	0.0881	0.0001	0.0111	0.0404	0.0099	0.7563
	(0.0099)	(0.0336)	(0.0398)	(0.0008)	(0.0253)	(0.0154)	(0.0048)	(0.2884)

NOTES: This table presents the impact on conditional *variances* given a change in the variables, while holding other variables constant; that is, the coefficients are taken from the VEC-representation. Thus the interaction effect is not examined here. The impact surfaces presented throughout the paper take interaction fully into account. The model here is the one where price of risk with respect to *firm* (as opposed to *stock*) is assumed to be constant. Standard errors are in parentheses.

Table 6: Impact of Variables on Conditional Covariances

Equation	$\sigma^2_{M,t-1}$	$\sigma_{Mi,t-1}$	$\varepsilon^2_{M,t-1}$	$\varepsilon_{i,t-1}\varepsilon_{M,t-1}$	$\eta^2_{M,t-1}$	$\eta_{i,t-1}\eta_{M,t-1}$	$10^{-2} LR^2_{M,t-1}$	$10^{-2} LR_{i,t-1} LR_{M,t-1}$
High	0.2401	0.5218	0.0168	0.0485	0.1775	-0.0122	0.0010	-0.0002
	(0.1623)	(0.1457)	(0.0400)	(0.0281)	(0.1072)	(0.0618)	(0.0051)	(0.0011)
Medium	-0.0519	0.7675	-0.0388	0.0812	0.2991	0.0119	0.0000	-0.0001
	(0.0508)	(0.0440)	(0.0226)	(0.0328)	(0.0952)	(0.0581)	(0.0001)	(0.0003)
Low	-0.0925	0.8086	0.0755	0.0018	0.0481	0.0919	0.0001	-0.0012
	(0.0365)	(0.0364)	(0.0380)	(0.0134)	(0.0622)	(0.0238)	(0.0007)	(0.0061)

NOTES: This table presents the impact on conditional *covariances* given a change in the variables, while holding other variables constant; that is, the coefficients are taken from the VEC-representation. Thus the interaction effect is not examined here. The impact surfaces presented throughout the paper take interaction fully into account. The model here is the one where price of risk with respect to *firm* (as opposed to *stock*) is assumed to be constant. Standard errors are in parentheses.

Table 7: Capitalization and Beta of Portfolios

PORTFOLIO	Capitalization# (¥, 10^{11})	Unconditional Beta	Conditional Beta Max	Min	Mean	Std. Dev.
High leverage	46.23	1.1122	1.4419	0.8445	1.1751	0.1113
Medium leverage	9.19	1.1088	1.4989	0.0848	1.0065	0.2037
Low leverage	28.74	0.6244	1.1234	0.2432	0.7314	0.1413
Large size – High leverage	71.19	1.1766	1.7055	0.7779	1.3114	0.2128
Large size – Medium leverage	63.46	0.8825	1.3683	0.5512	0.9901	0.1789
Large size – Low leverage	63.34	0.7733	1.3388	0.5138	0.8564	0.1456
Small size – High leverage	7.08	0.6963	1.9124	0.0078	0.5039	0.3520
Small size – Medium leverage	3.56	1.0945	1.6350	0.2758	0.9980	0.1876
Small size – Low leverage	5.13	1.0495	1.4733	0.5159	0.9505	0.1724

NOTES: This table presents capitalizations, unconditional betas and conditional betas of all the portfolios examined in this paper. Unconditional betas are computed using the sample variance and covariance of portfolio returns. Conditional betas are generated using the estimated BEKK model.

#: Capitalization is the average over sample period covered in the study (Jan 1985 to June 1994).

Table 8: Beta Tests: RMSE and the Ball and Kothari Regression

	Panel A: RMSE tests of beta models				Panel B: Ball and Kothari Regression		
	Time Varying Beta Model	Time-varying Price of Risk Model	Unconditional Beta Model	Rolling Beta	J=13	J=26	J=52
High Leverage	28.65	28.07	28.53	28.56	0.2458	0.2291	0.1918
			28.70	28.70	(0.0625)	(0.0468)	(0.0392)
Med. Leverage	34.12	34.20	34.08	34.02	-0.2808	0.0249	0.1046
			34.14	34.13	(0.1226)	(0.0990)	(0.0889)
Low Leverage	24.13	24.24	24.04	24.05	-0.8057	-0.5049	-0.3303
			24.16	24.16	(0.0550)	(0.0472)	(0.0373)

NOTES: Panel A compares the annualized root mean square error (RMSE) of our model with those of the time varying price of risk model, the unconditional beta model and the rolling beta model. The unconditional beta model uses the sample beta whereas the rolling beta model uses a rolling sample of 260 observations in estimating beta. Note that our model and the time-varying price of risk model need to predict both market risk premium and beta. Thus, in order to make the comparison meaningful, we use the predicted value of market risk premium from our model in computing the root mean square errors for the unconditional beta model and the rolling beta model. The values on the second line of the unconditional beta and rolling beta models are the RMSE where the average market excess return is used to proxy for the market risk premium. The first 260 observations are dropped to avoid the dependence on start-up values.

Panel B presents the k_J estimates of the Ball and Kothari regression (see equation 14). Standard errors are in parentheses.

Table 9a: Impact of Variables on Conditional Variances (Size Effect: Small Firms)

Equation	$\sigma^2_{M,t-1}$	$\sigma^2_{i,t-1}$	$\varepsilon^2_{M,t-1}$	$\varepsilon^2_{i,t-1}$	$\eta^2_{M,t-1}$	$\eta^2_{i,t-1}$	$10^{-2}\,LR^2_{M,t-1}$	$10^{-2}\,LR^2_{i,t-1}$
Market	0.8006		0.0208		0.2117		0.0000	
	(0.1027)		(0.0196)		(0.0188)		(0.0015)	
High	0.0002	0.8495	0.0046	0.1193	0.0066	0.0992	0.0586	0.0377
	(0.0013)	(0.0410)	(0.0025)	(0.0186)	(0.0077)	(0.0086)	(0.0129)	(0.0148)
Medium	1.3685	0.0003	0.0931	0.1180	0.0456	0.0898	0.0728	0.0519
	(0.0857)	(0.0134)	(0.0087)	(0.0042)	(0.0103)	(0.0031)	(0.0122)	(0.0193)
Low	0.0675	0.4548	0.0062	0.0621	0.0681	0.0764	0.0003	0.0448
	(0.0407)	(0.0514)	(0.0012)	(0.0097)	(0.0176)	(0.0089)	(0.0078)	(0.0019)

NOTES: This table presents, for the *small* firm leverage portfolios, the impact on conditional *variances* given a change in the variables, while holding other variables constant; that is, the coefficients are taken from the VEC-representation. Thus the interaction effect is not examined here. The impact surfaces presented throughout the paper take interaction fully into account. The model here is the one where price of risk with respect to *firm* (as opposed to *stock*) is assumed to be constant. Standard errors are in parentheses.

Table 9b: Impact of Variables on Conditional Variances (Size Effect: Large Firms)

Equation	$\sigma^2_{M,t-1}$	$\sigma^2_{i,t-1}$	$\varepsilon^2_{M,t-1}$	$\varepsilon^2_{i,t-1}$	$\eta^2_{M,t-1}$	$\eta^2_{i,t-1}$	$10^{-2} LR^2_{M,t-1}$	$10^{-2} LR^2_{i,t-1}$
Market	0.7943		0.0692		0.1540		0.0001	
	(0.0415)		(0.0085)		(0.0100)		(0.0013)	
High	0.0033	0.9404	0.0302	0.0021	0.0324	0.0237	0.8425	0.0351
	(0.0028)	(0.0104)	(0.0047)	(0.0022)	(0.0050)	(0.0043)	(0.0275)	(0.0077)
Medium	0.0034	0.9518	0.0062	0.0184	0.0235	0.0334	0.0093	0.0001
	(0.0020)	(0.0177)	(0.0024)	(0.0037)	(0.0041)	(0.0059)	(0.0026)	(0.0018)
Low	0.0001	0.8067	0.0728	0.0102	0.0014	0.1198	0.0355	0.0009
	(0.0018)	(0.0562)	(0.0090)	(0.0032)	(0.0017)	(0.0112)	(0.0067)	(0.0013)

NOTES: This table presents, for the *large* firm leverage portfolios, the impact on conditional *variances* given a change in the variables, while holding other variables constant; that is, the coefficients are taken from the VEC-representation. Thus the interaction effect is not examined here. The impact surfaces presented throughout the paper take interaction fully into account. The model here is the one where price of risk with respect to *firm* (as opposed to *stock*) is assumed to be constant. Standard errors are in parentheses.

Table 10a: Impact of Variables on Conditional Covariances
(Size Effect: Small Firms)

Equation	$\sigma^2_{M,t-1}$	$\sigma_{Mi,t-1}$	$\varepsilon^2_{M,t-1}$	$\varepsilon_{i,t-1}\varepsilon_{M,t-1}$	$\eta^2_{M,t-1}$	$\eta_{i,t-1}\eta_{M,t-1}$	$10^{-2} LR^2_{M,t-1}$	$10^{-2} LR_{i,t-1}LR_{M,t-1}$
High	-0.0112	0.8247	-0.0097	0.0498	0.0375	0.1449	-0.0010	0.0008
	(0.0449)	(0.0717)	(0.0023)	(0.0272)	(0.0203)	(0.0040)	(0.0437)	(0.0353)
Medium	1.0467	0.0143	-0.0440	0.0495	0.0983	0.1379	0.0011	-0.0010
	(0.0996)	(0.3752)	(0.0228)	(0.0229)	(0.0150)	(0.0069)	(0.0490)	(0.0415)
Low	0.2324	0.6034	-0.0114	0.0359	0.1201	0.1272	0.0001	0.0009
	(0.0849)	(0.0725)	(0.0045)	(0.0196)	(0.0108)	(0.0123)	(0.0043)	(0.0384)

NOTES: This table presents, for the *small* firm leverage portfolios, the impact on conditional *covariances* given a change in the variables, while holding other variables constant; that is, the coefficients are taken from the VEC-representation. Thus the interaction effect is not examined here. The impact surfaces presented throughout the paper take interaction fully into account. The model here is the one where price of risk with respect to *firm* (as opposed to *stock*) is assumed to be constant. Standard errors are in parentheses.

Table 10b: Impact of Variables on Conditional Covariances (Size Effect: Large Firms)

Equation	$\sigma^2_{M,t-1}$	$\sigma_{Mi,t-1}$	$\varepsilon^2_{M,t-1}$	$\varepsilon_{i,t-1}\varepsilon_{M,t-1}$	$\eta^2_{M,t-1}$	$\eta_{i,t-1}\eta_{M,t-1}$	$10^{-2} LR^2_{M,t-1}$	$10^{-2} LR_{i,t-1}LR_{M,t-1}$
High	-0.0509	0.8643	0.0457	0.0120	0.0706	0.0604	-0.0083	0.0017
	(0.0204)	(0.0205)	(0.0048)	(0.0068)	(0.0062)	(0.0062)	(0.0652)	(0.0135)
Medium	-0.0518	0.8695	0.0207	0.0357	0.0602	0.0717	0.0009	-0.0001
	(0.0144)	(0.0292)	(0.0047)	(0.0048)	(0.0058)	(0.0067)	(0.0068)	(0.0002)
Low	-0.0108	0.8005	0.0709	-0.0266	-0.0148	0.1358	0.0017	0.0003
	(0.0656)	(0.0153)	(0.0074)	(0.0038)	(0.0087)	(0.0076)	(0.0135)	(0.0023)

NOTES: This table presents, for the *large* firm leverage portfolios, the impact on conditional *covariances* given a change in the variables, while holding other variables constant; that is, the coefficients are taken from the VEC-representation. Thus the interaction effect is not examined here. The impact surfaces presented throughout the paper take interaction fully into account. The model here is the one where price of risk with respect to *firm* (as opposed to *stock*) is assumed to be constant. Standard errors are in parentheses.

Figure 1: News Impact at the Market Level and the Firm Level

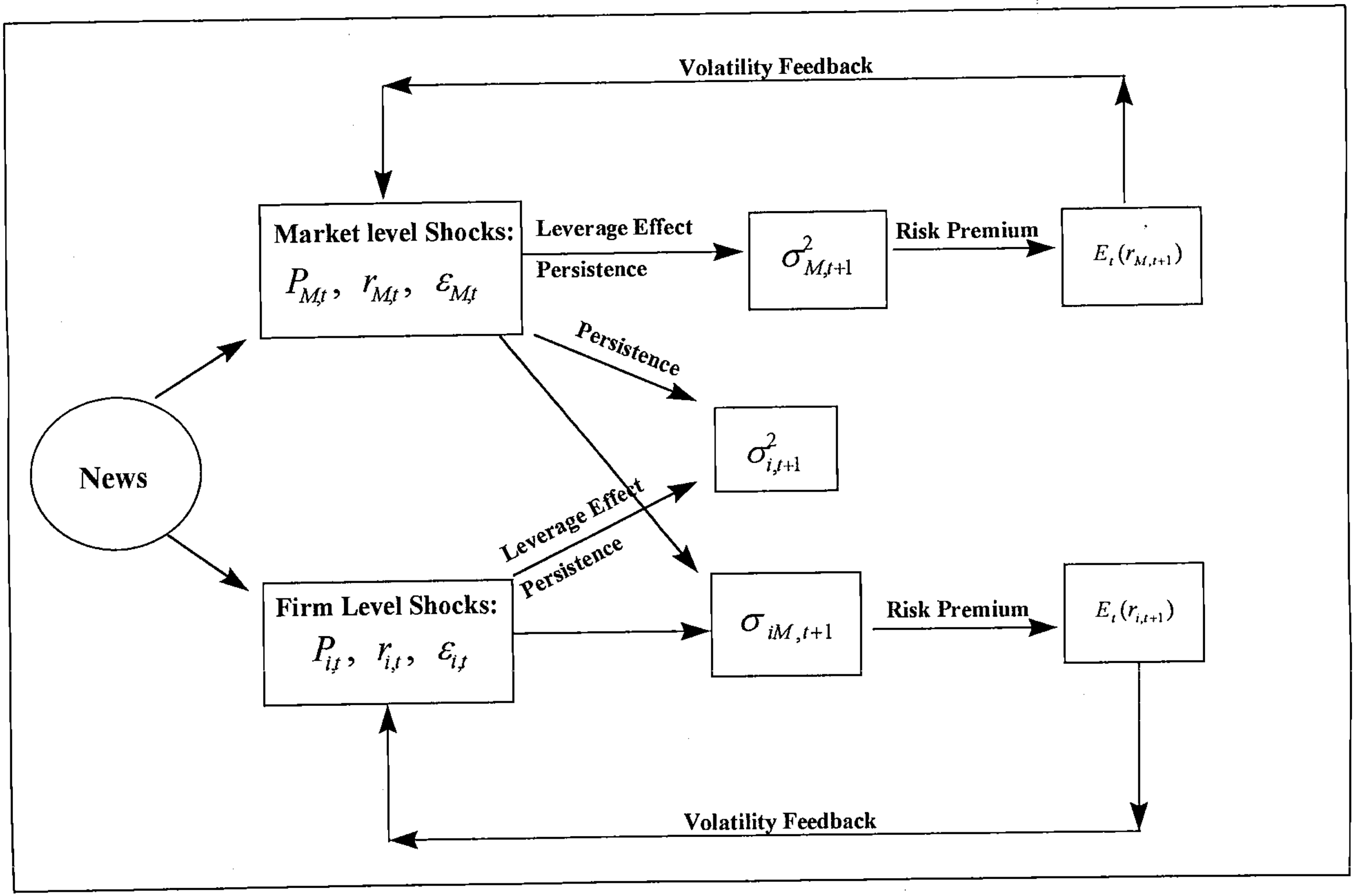


Figure 2: Conditional Variances for Market and Leverage Portfolios

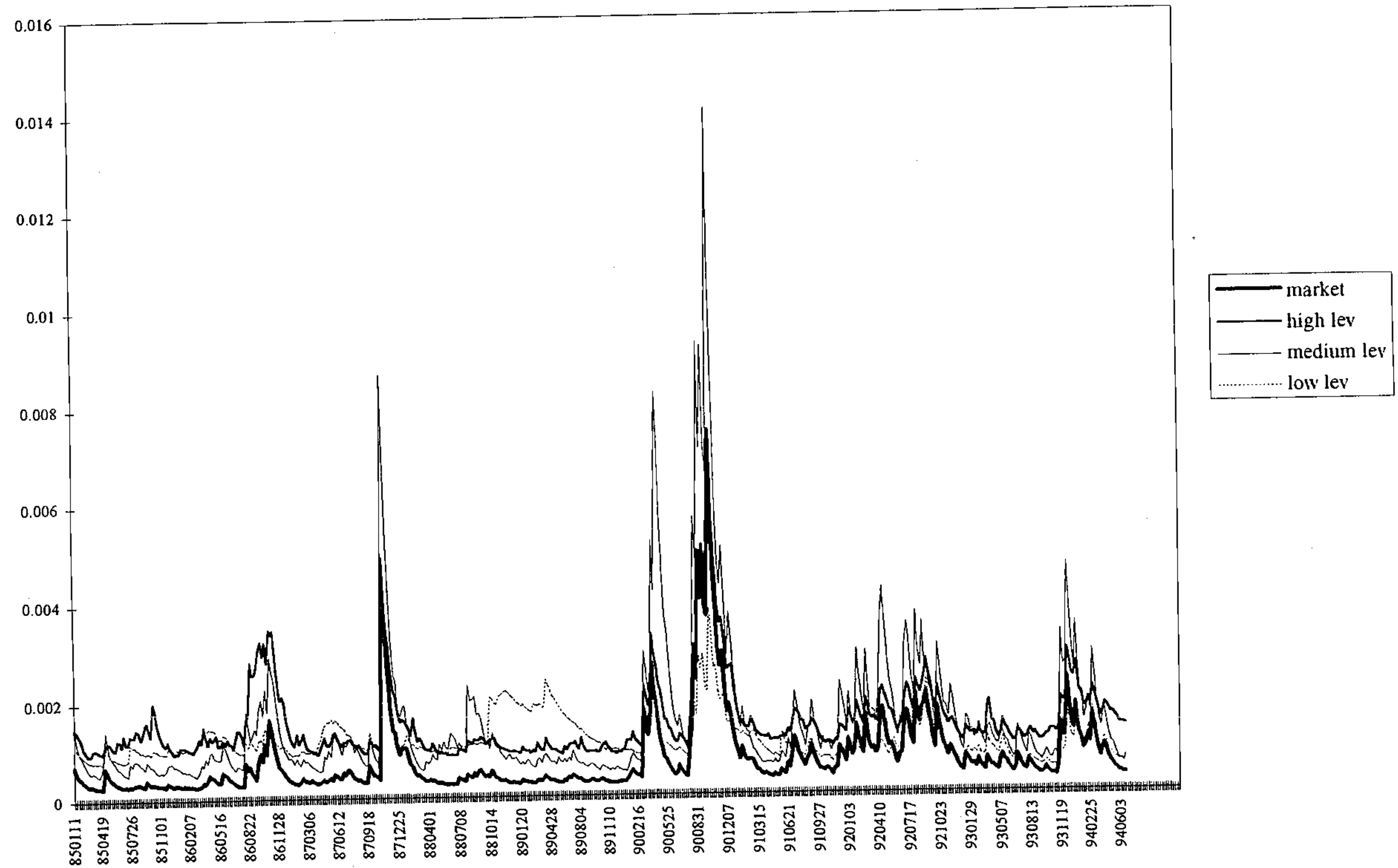


Figure 3: Time Varying Risk Premium of the Market

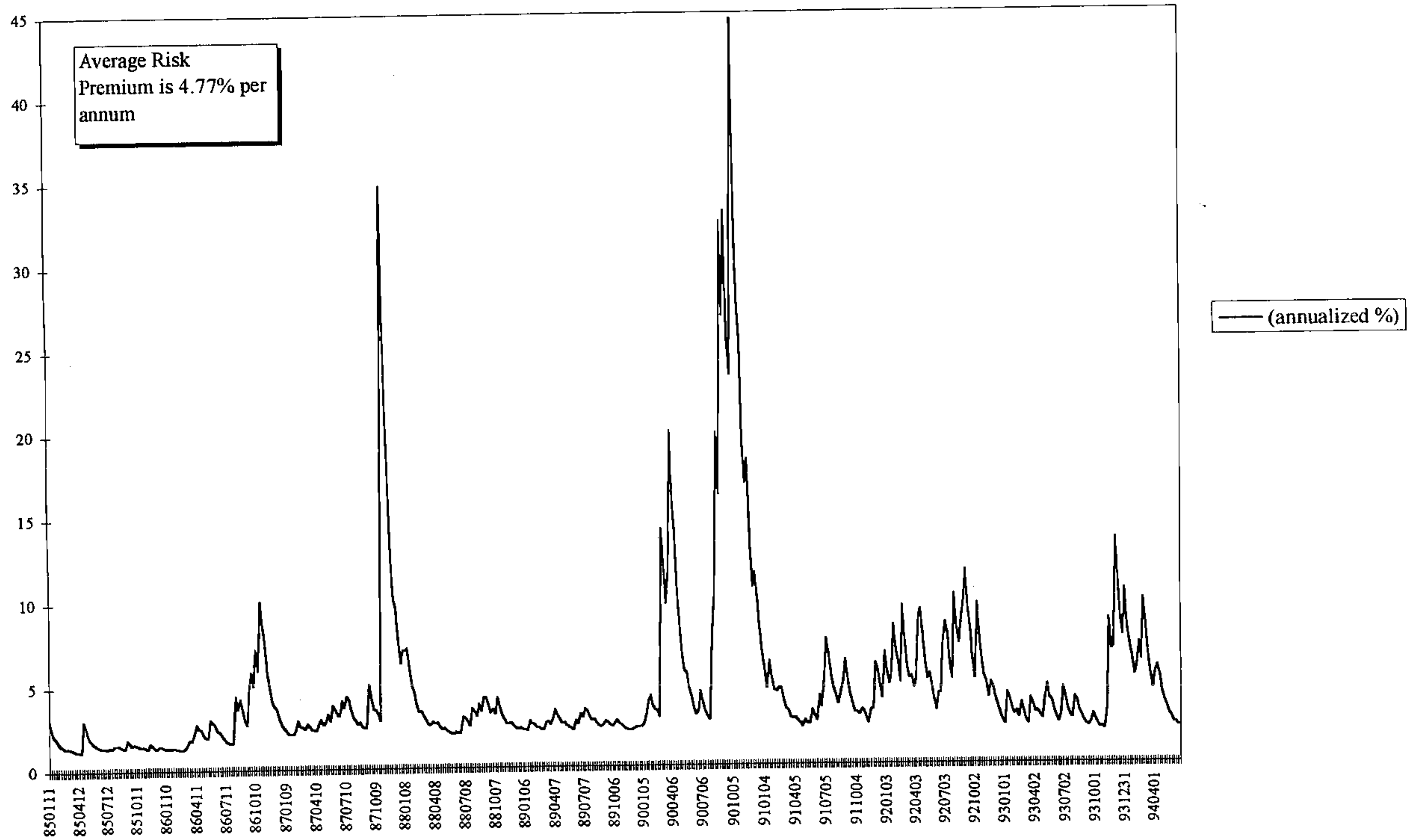


Figure 4-a: Market Conditional Variance Response to Market Shocks

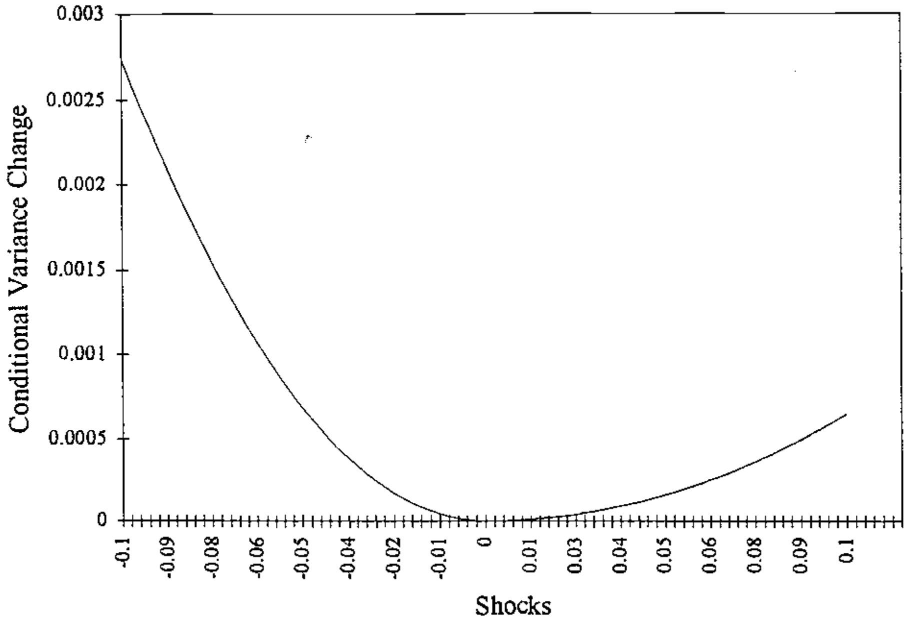


Figure 4-b: High Leverage Portfolio Conditional Variance Response to Shocks

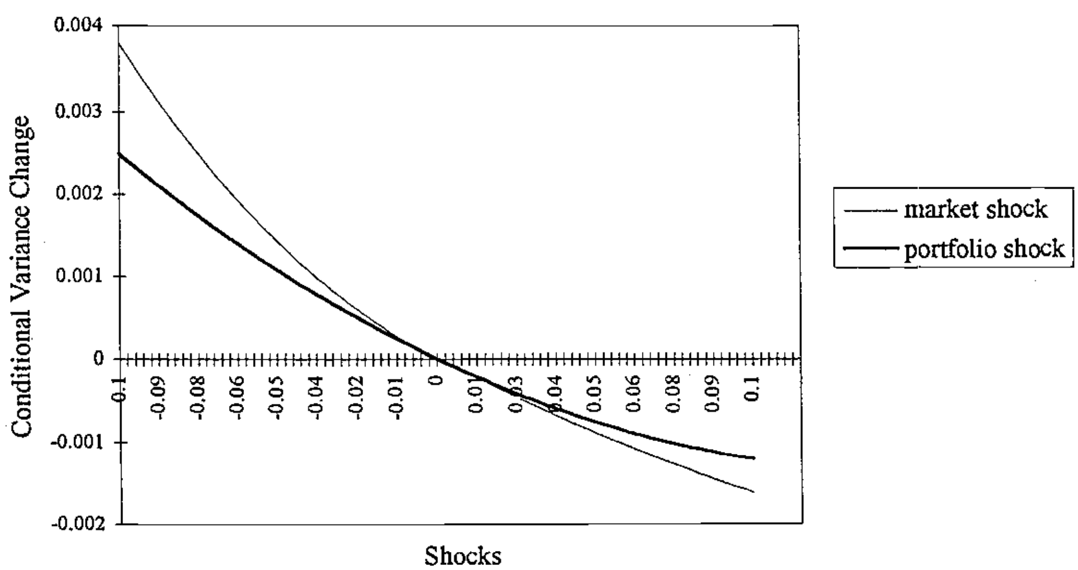


Figure 4-c: Medium Leverage Portfolio Conditional Variance Response to Shocks

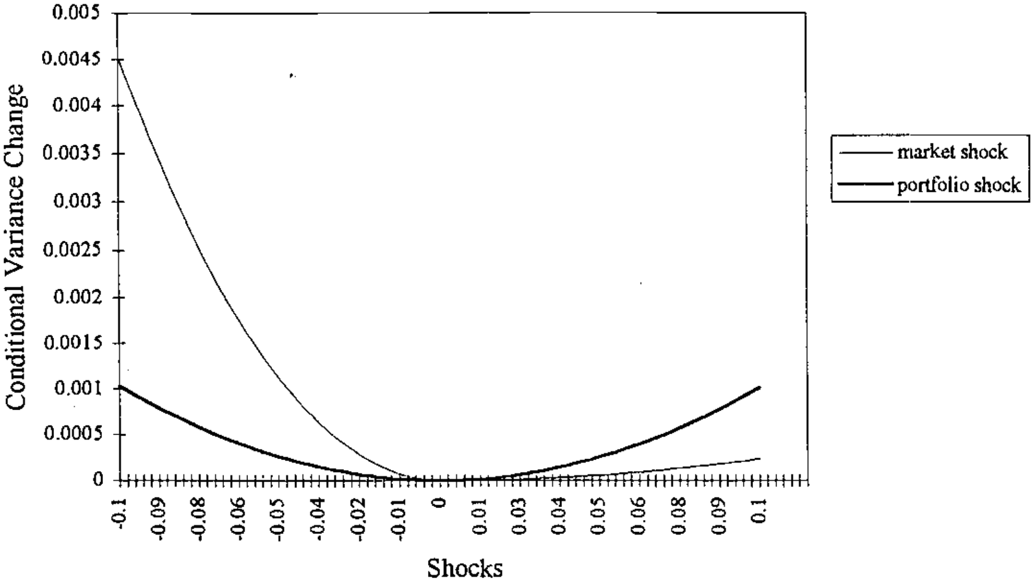


Figure 4-d: Low Leverage Portfolio Conditional Variance Response to Shocks

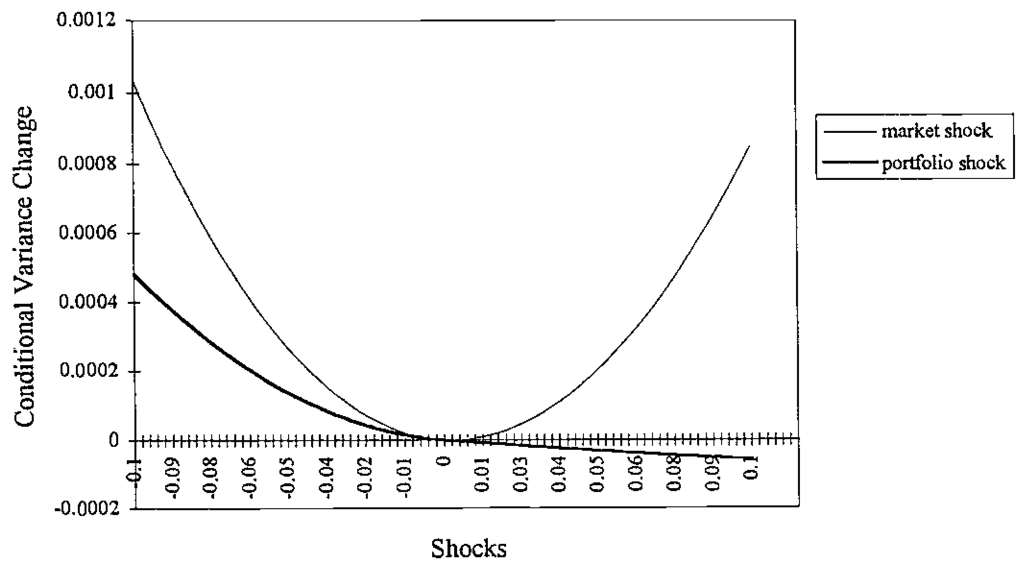


Figure 5-a: Market Variance Impact Surface

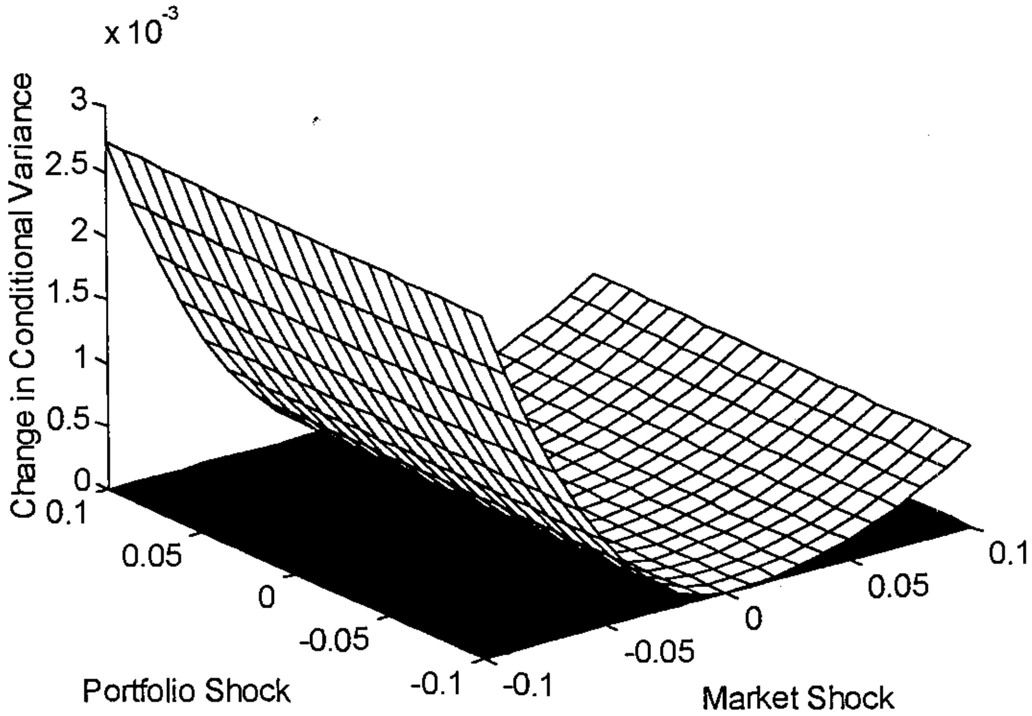


Figure 5-b: High Lev. Portfolio Variance Impact Surface

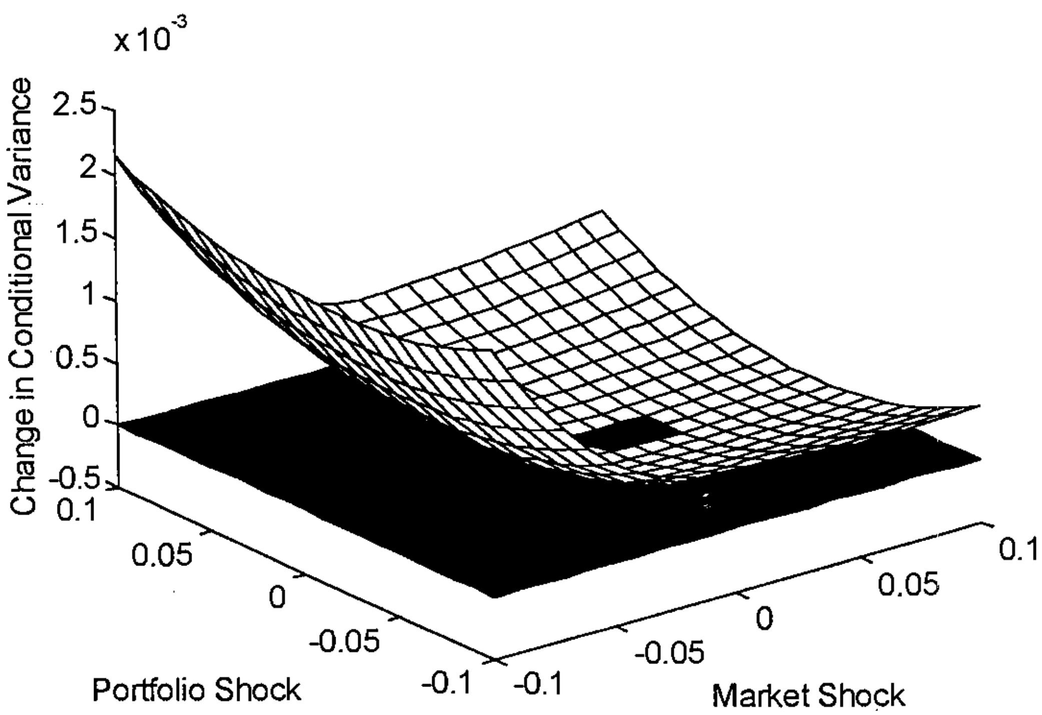


Figure 5-c: Med. Lev. Portfolio Variance Impact Surface

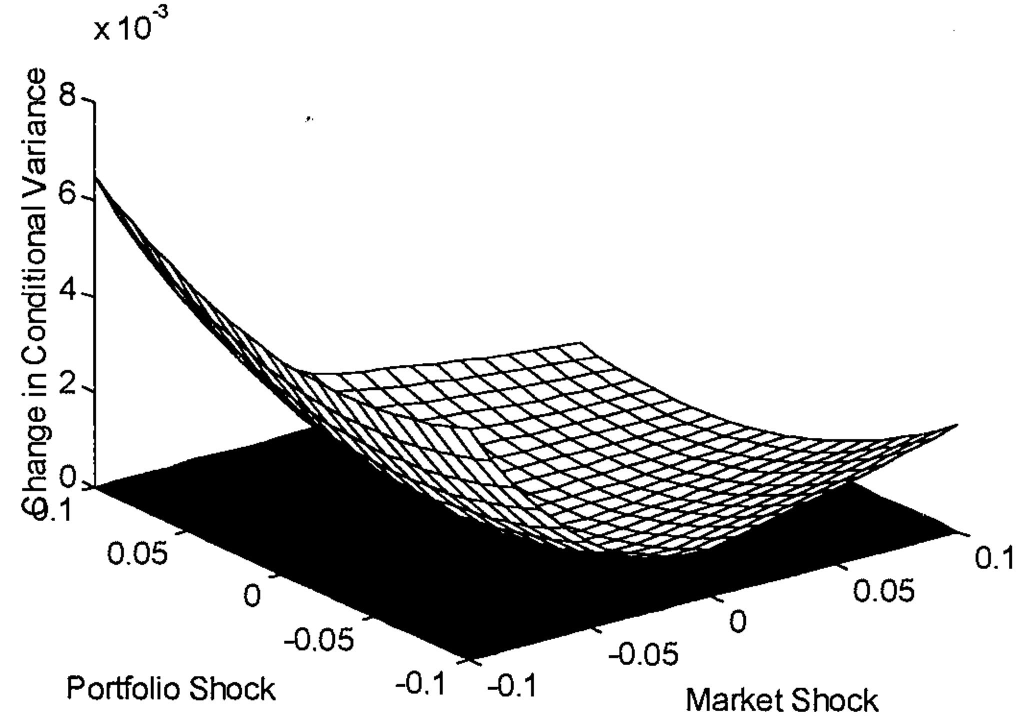


Figure 5-d: Low Lev. Portfolio Variance Impact Surface

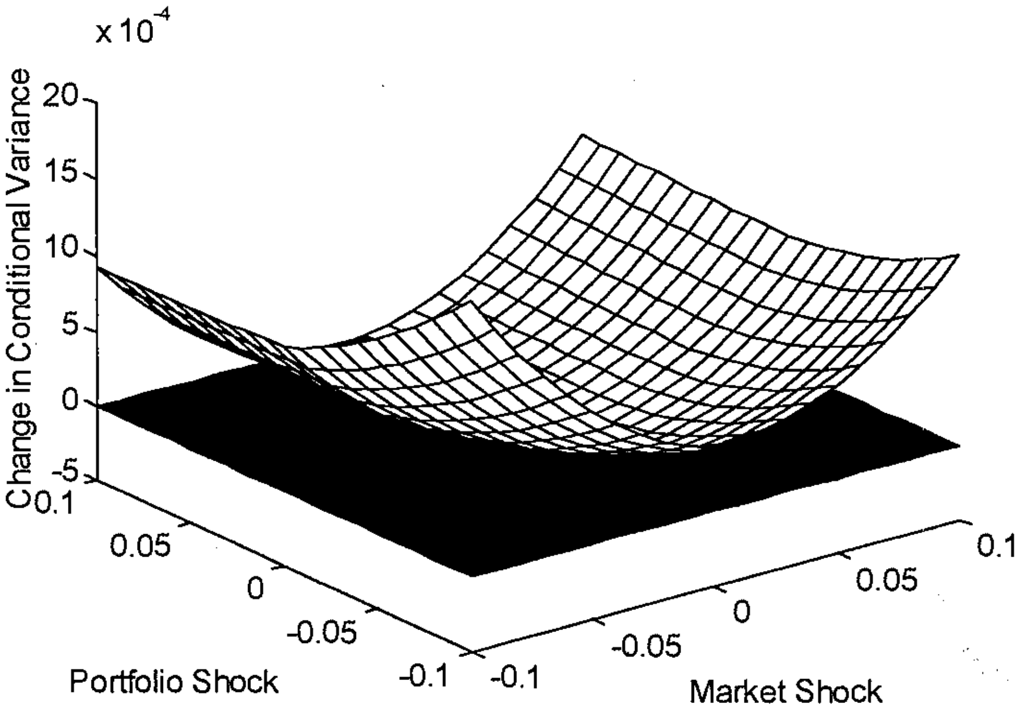


Figure 6: Conditional Covariances between Market and Leverage Portfolios

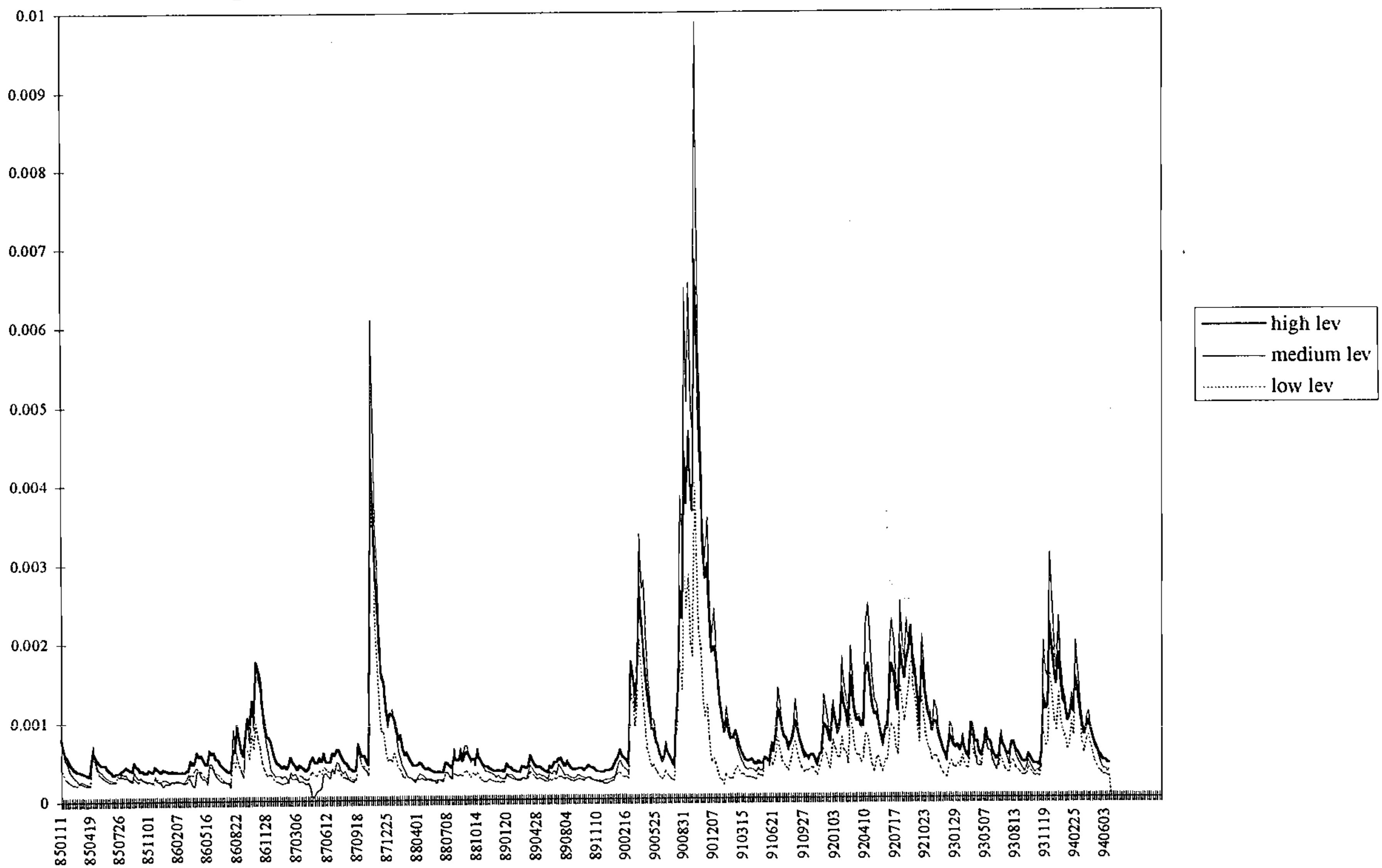


Figure 7: Conditional Covariance Response to Market Return Shocks

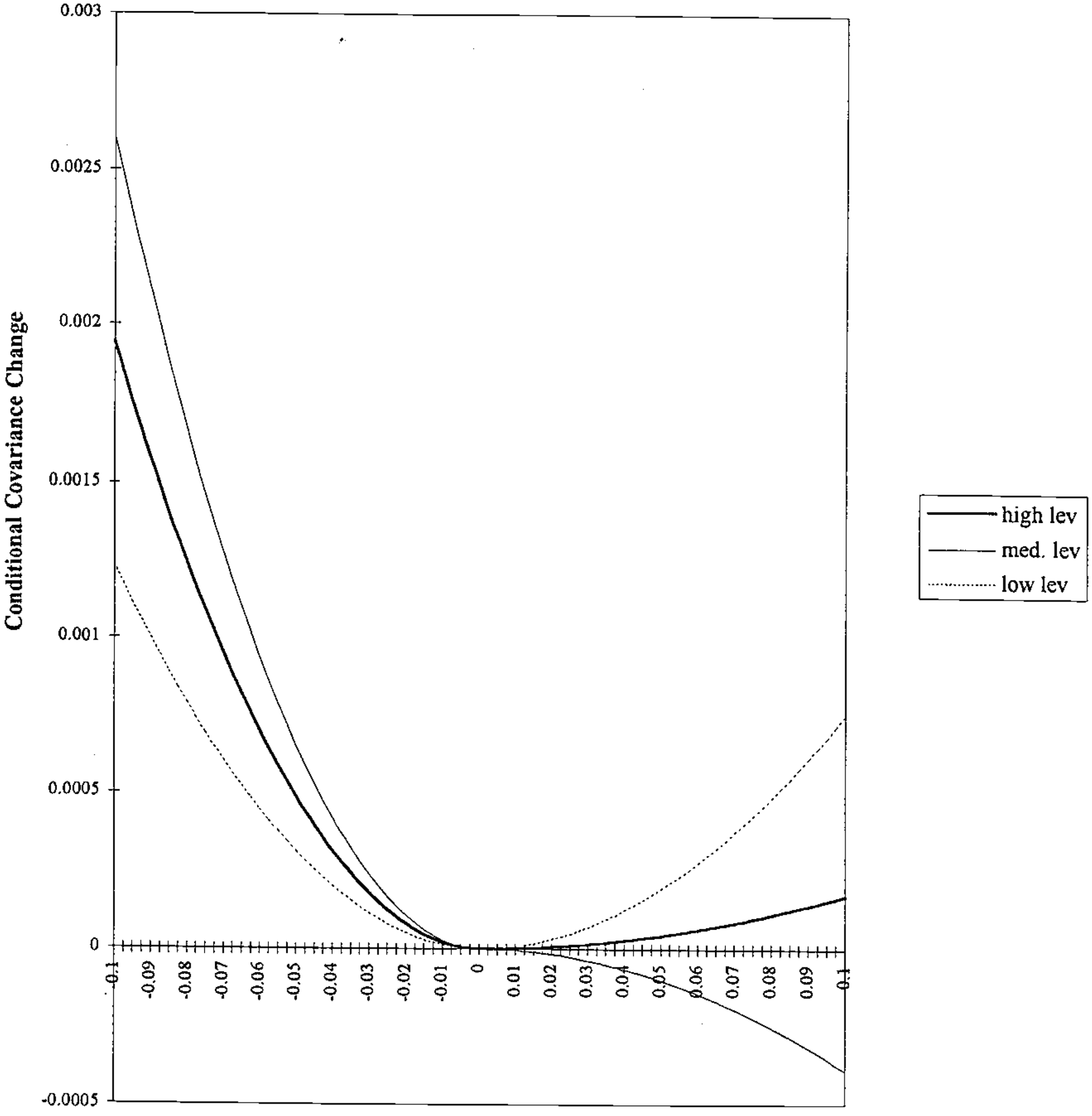


Figure 8-a: High Lev. Portfolio Covariance Impact Surface

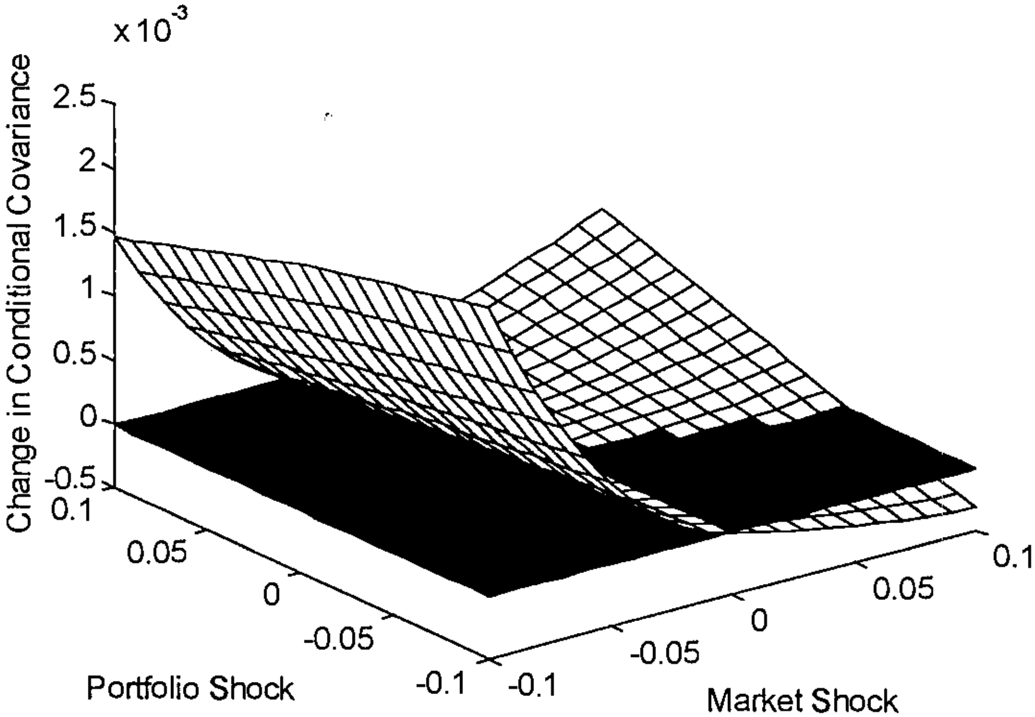


Figure 8-b: Med. Lev. Portfolio Covariance Impact Surface

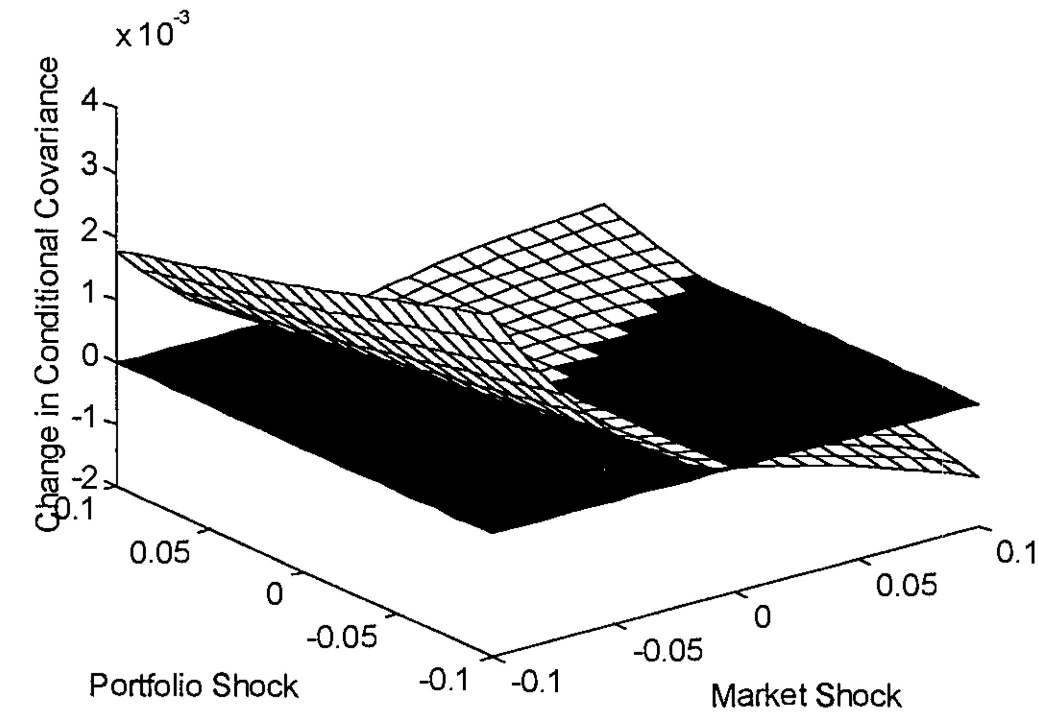


Figure 8-c: Low Lev. Portfolio Covariance Impact Surface

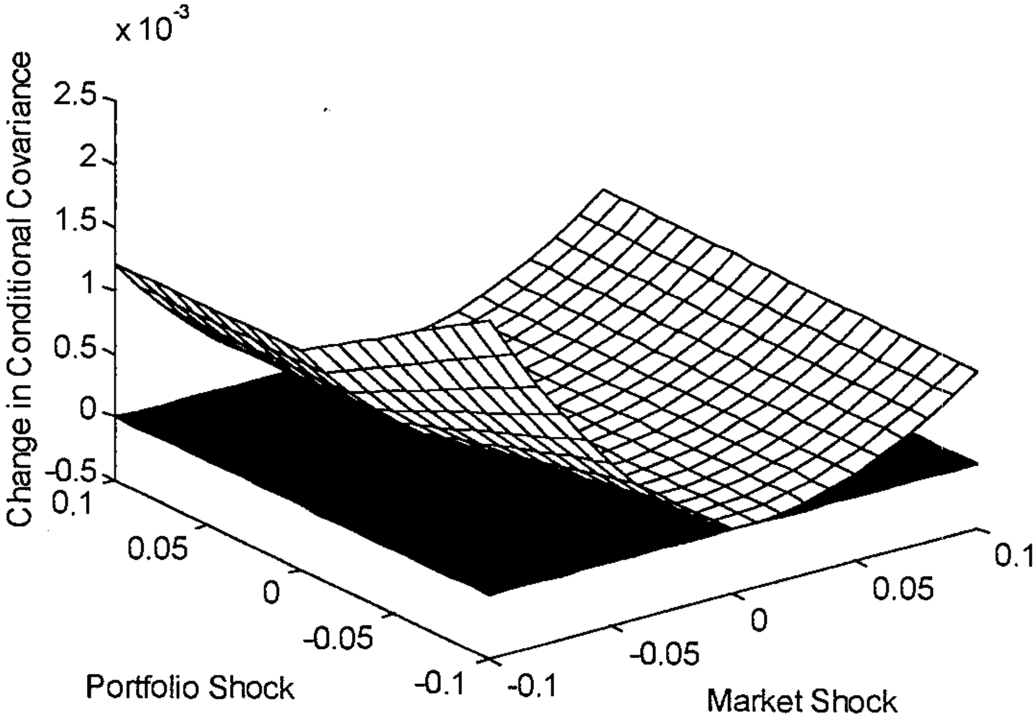


Figure 9: Conditional Betas of Leverage Portfolios

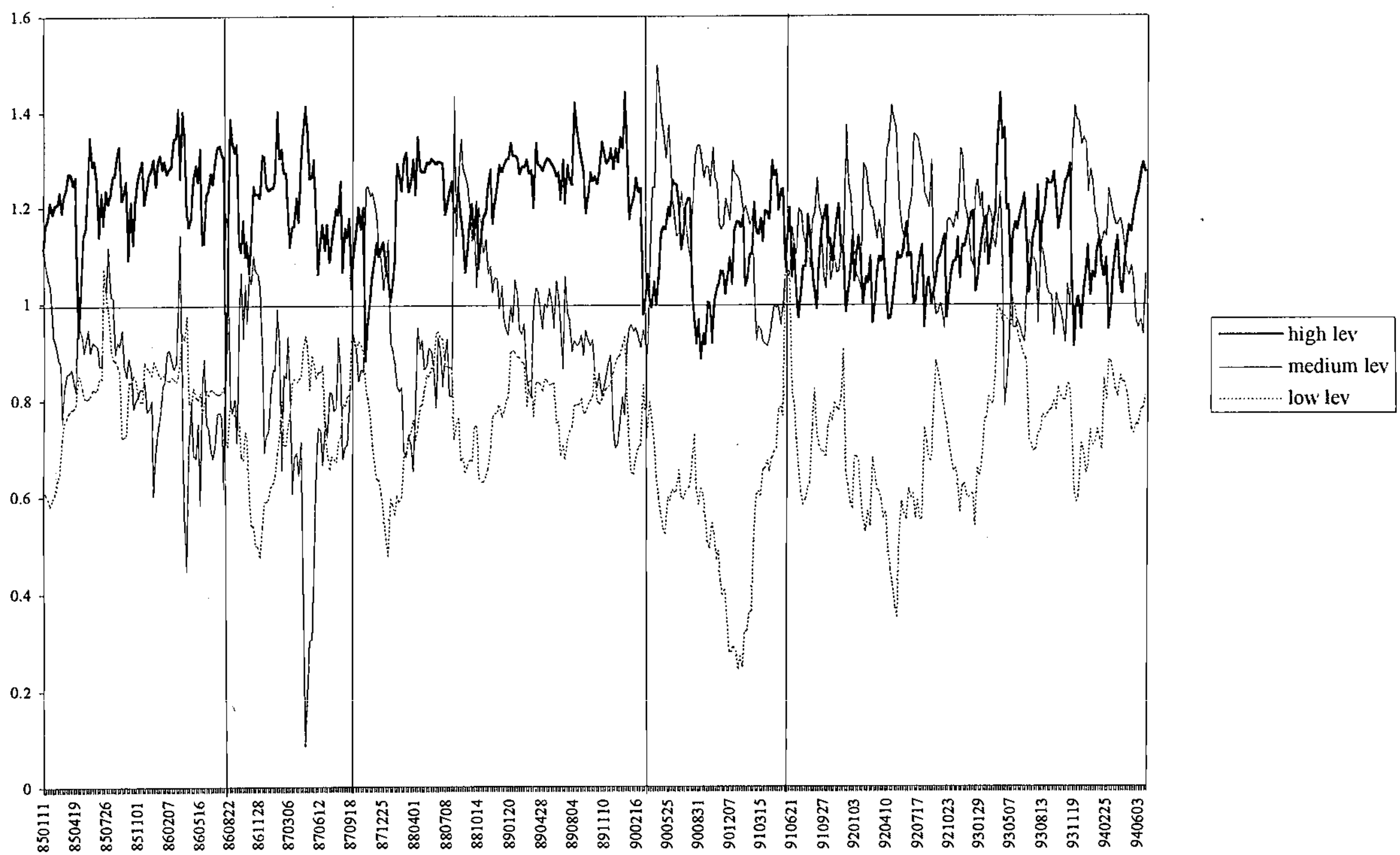


Figure 10-a: High Lev. Portfolio Beta Impact Surface

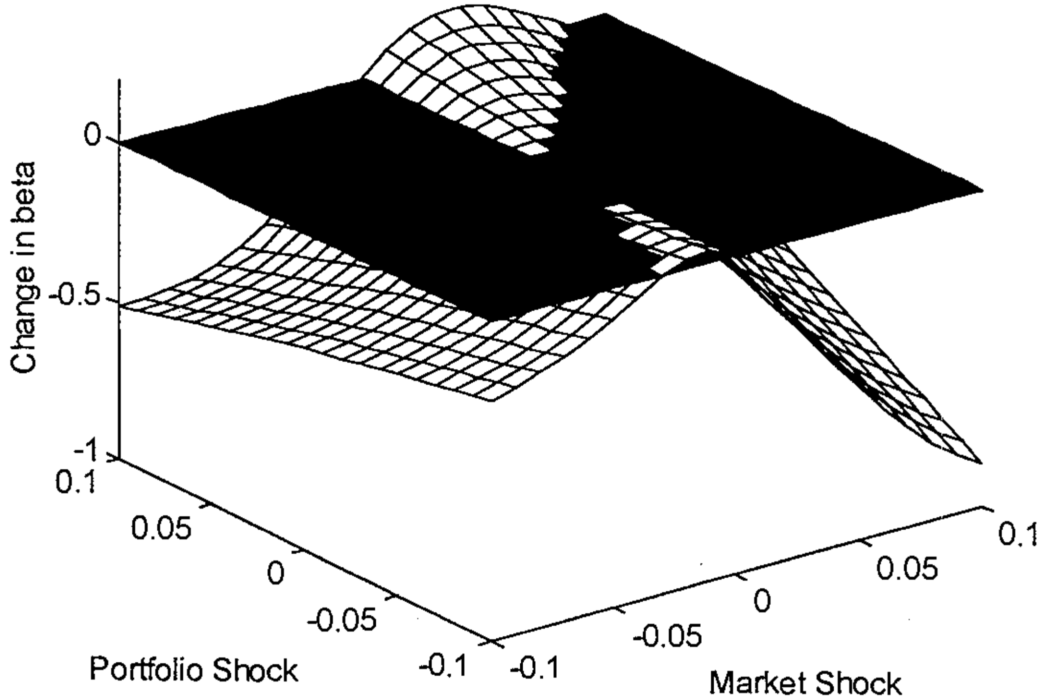


Figure 10-b: Med Lev. Portfolio Beta Impact Surface

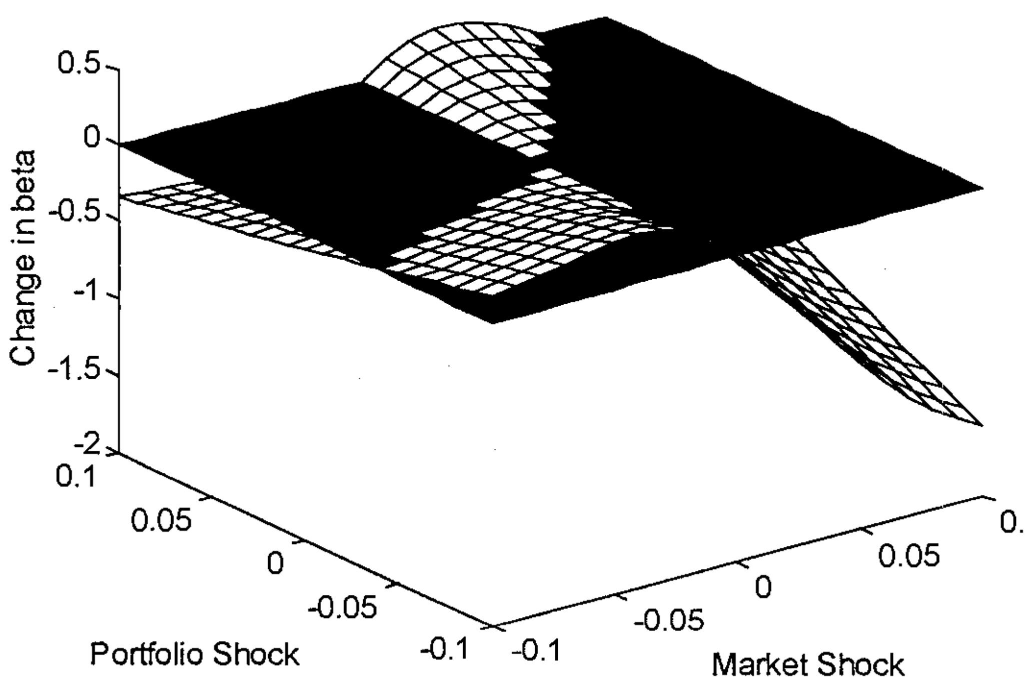
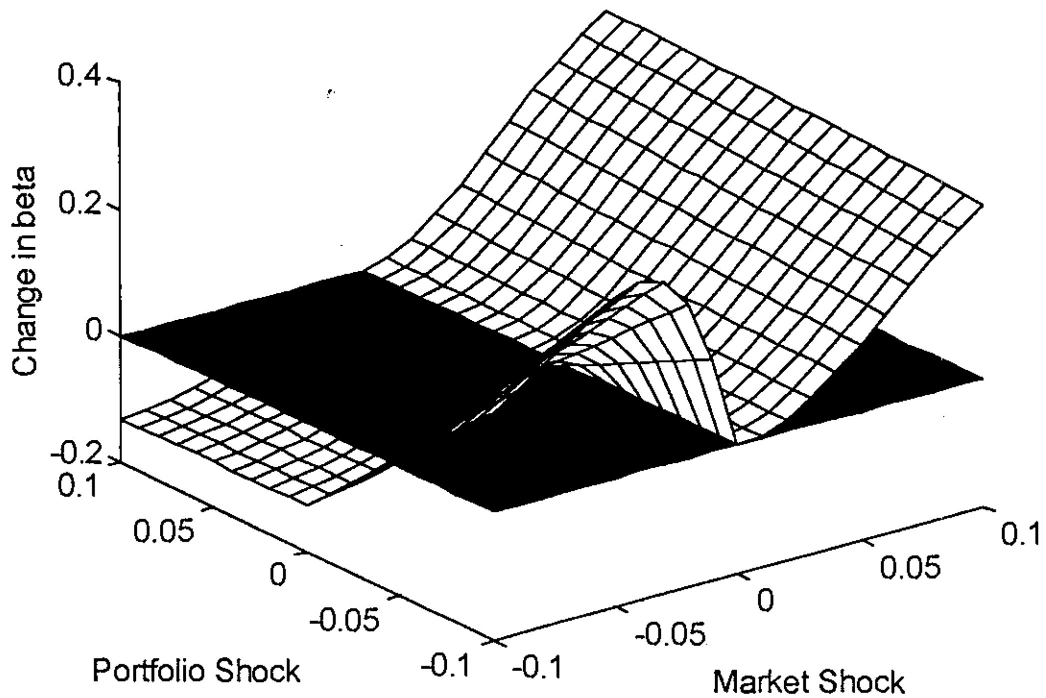


Figure 10-c: Low Lev. Portfolio Beta Impact Surface



APPENDIX:

Estimated Variance Covariance Equation

$$\Sigma_t = \mathrm{E}\left(\varepsilon_t \varepsilon_t' \middle| I_{t-1}\right) = \Omega\Omega' + B\Sigma_{t-1}B' + C\varepsilon_{t-1}\varepsilon_{t-1}'C' + D\eta_{t-1}\eta_{t-1}'D' + Gl_{t-1}l_{t-1}'G'$$

	Parameters				Standard Errors			
Ω	0.0079441	0	0	0	0.0013	0	0	0
	0.0117213	0.0159199	0	0	0.0035735	0.0024673	0	0
	0.0079926	-0.000428	0.0060023	0	0.0017454	0.000904	0.0016703	0
	0.0079048	-0.003092	-0.001487	0.0030638	0.0018376	0.0012561	0.0014492	0.0018565
B	-0.857736	0	0	0	0.0345051	0	0	0
	-0.279977	-0.608332	0	0	0.18638	0.167234	0	0
	0.0605615	0	-0.89481	0	0.0605369	0	0.0349734	0
	0.10779	0	0	-0.942748	0.0458295	0	0	0.0178208
C	0.254448	0	0	0	0.0812707	0	0	0
	0.0659186	0.190547	0	0	0.144745	0.0921017	0	0
	-0.152627	0	0.319019	0	0.115724	0	0.0566804	0
	0.296883	0	0	0.0072308	0.0669847	0	0	0.0529013
D	0.457104	0	0	0	0.0856168	0	0	0
	0.388415	-0.026775	0	0	0.195357	0.13534	0	0
	0.654319	0	0.0259551	0	0.144533	0	0.124766	0
	0.105122	0	0	0.201077	0.120399	0	0	0.0382485
G	0.0136816	0	0	0	0.0698543	0	0	0
	7.26529	-1.64993	0	0	2.01245	0.471163	0	0
	0.164107	0	-0.460715	0	0.334358	0	0.58614	0
	0.995647	0	0	-8.69641	0.238744	0	0	1.65841

NOTES: This is the model where price of risk with respect to *firm* is assumed to be constant.

Estimated Correlation Coefficients between Leverage Ratios and Shock Terms

Variables	market	high	medium	low
$\mathrm{Corr}(l_t, \varepsilon_t)$	-0.034931	-0.032482	-0.086619	0.00888
$\mathrm{Corr}(l_t, \eta_t)$	0.038775	0.004192	0.10947	-0.013569

Firms in the Leverage Portfolios

Portfolio	Firms
Low Leverage	Teikoku Oil
	Pioneer Electronic
	Shimura Kako
	Fuji Photo Film
	Sankyo
Medium Leverage	NTN
	Shinagawa Refractories
	Nitto Beseki
	Nachi-Fujikoshi
	Toyobo
High Leverage	Mitsubishi
	Itochu
	Mitsui & Co.
	Marubeni
	Nippon Shinpan