Leverage and Asymmetric Volatility: The Firm Level Evidence

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August 27, 2007

ABSTRACT

The relative statistical and economic significance of the leverage and feedback effects on firm level equity volatility is still an open issue in the finance literature. We provide a dynamic framework to investigate both effects simultaneously. An important feature of our methodology is that we allow leverage, volatility and risk premia to influence each other over time. Using the intersection of all firms in CRSP and COMPUSTAT from 1971 to 2005, we perform our analysis using a Panel Vector Autoregression (PVAR) model. We find a much larger leverage effect than reported in Christie (1982). Interestingly, we also find that the leverage effect accumulates over time, rendering it up to five times larger than a static model would predict.

JEL Classification: C33
Keywords: Financial leverage, stock volatility, panel data, PVAR

*We would like to thank Graciela Kaminsky, Xiangdong Long, Takashi Yamagata, and seminar participants at Cambridge University and the 2007 North American Summer Meeting of the Econometric Society for helpful suggestions and comments. The last two authors also acknowledge the financial support from the Michel J. Coles College of Business at Kennesaw State University. All remaining errors are our own. Jan Ericsson can be reached at Jan.Ericsson@mcgill.ca. Xiao Huang can be reached at xhuang3@kennesaw.edu. Address correpondence to Stefano Mazzotta, Department of Economics & Finance, Coles College of Business Kennesaw State University, 1000 Chastain Road, #0403 Kennesaw, GA 30144-5591. smazzott@kennesaw.edu. Phone: (770) 423-6341. Fax: (770) 499-3209.

Although there is a considerable literature on the modeling of equity volatilities, the relative importance of the various theoretically identified determinants and their importance is still an open controversy. In particular, the importance of the leverage effect identified by Black (1976) is not yet fully understood. In this paper, we provide additional evidence based on a large scale firm level study of equity volatility in an econometric model which allows for dynamic linkages between firm specific equity volatility, financial leverage, and time varying risk premia.

Our main finding is that financial leverage is an economically more significant determinant of equity volatilities than previous work has documented, and that its effect accumulates over time. Our study suggests that past results may be due to not fully allowing for the endogenous nature of the relationship between leverage and business risk - the choice of leverage and volatility is a joint decision for a firm.

Christie (1982) documents that equity variance has a strong positive association with financial leverage and the negative elasticity of volatility with respect to the level of stock prices should be ascribed to financial leverage to a significant degree. This result is not without controversy. Figlewski and Wang (2000) use both returns and directly measured leverage to examine the effect of financial leverage as it applies to the individual stocks in the S&P100 (OEX) index, and to the index itself. They find a strong asymmetry associated with falling stock prices, but also numerous anomalies that call into question financial leverage changes as a viable explanation. They conclude that the "leverage effect" is rather a "down market effect" that may have little direct connection to firm capital structure.

An alternative explanation for the observed relationship between stock price levels and volatility is attributed to time varying risk premia. Following an increase in volatility priced by investors, required equity returns should increase thus leading to an immediate drop in the equity value. This story, which argues a causality opposed to the financial leverage effect, has garnered support in the literature.[1] Bekaert and Wu (2000) argue that the leverage explanation is in itself not sufficient and that the alternative explanation, often known as the volatility feedback effect, is supported by the data. Duffee (1995) studies the relationship between returns and volatility in a large sample of U.S

[1] Brown, Harlow, and Tinic (1988) show that stock price reactions to unfavorable news events tend to be larger than reactions to favorable events, and attribute their findings to volatility feedback. Poterba and Summers (1986), on the other hand argue against volatility feedback by pointing out that changes in volatility are too short-lived to have a major effect on stock prices.

firms. He finds that the leverage effect is mainly due to the positive contemporaneous correlation between firm stock returns and firm stock return volatility; the correlation between returns and future volatility appears to be weak.

Given the mixed results in the literature, we construct, like Bekaert and Wu (2000), a model which allows for both channels between stock prices and volatility. To do so, we rely on a panel vector autoregressive framework to describe the dynamics of financial leverage, equity volatility, and risk premia. Our sample, an unbalanced panel, contains over 116,000 firm quarters during the period 1971-2005.[2] *To the best of our knowledge this is the first study at the individual firm level to consider both volatility feedback and leverage.* In addition, we believe the scale of the study to be unprecedented, particularly in the context of a dynamic econometric model.

To establish a benchmark, we begin by estimating a bivariate panel Vector Autoregression that nests the Christie (1982) model. In doing so, we document a similar but stronger relationship between equity volatility and the debt ratio. The coefficient estimates are economically more significant than in his study but they behave similarly across leverage quartiles. Our model allows for a bidirectional relationship between leverage and volatility, thus allowing for dynamic endogeneity between the two firm level choice variables, i.e. business risk and capital structure.

We find that this is important in that the effect on volatility of a change in leverage accumulates over time. Although the focus of our study is on the relationship between leverage and volatility, we study to what degree our results are dependent on the inclusion of time varying risk premia into the system. We are comforted to find that our parameter estimates are robust to allowing for an alternative explanation for the link between stock price levels and volatility.

To measure the accumulation of leverage and feedback effects, we use impulse response functions. Consider for example the lowest leverage quartile: the *immediate* effect of a one standard deviation shock to leverage is to increase the annualized volatility by about 2 per cent. However, the *cumulative* effect of the same shock to leverage over the next 12 quarters exceeds 10 per cent annualized volatility. In the highest leverage quartile the cumulative effect can exceed 50 per cent annualized volatility. The cumulative effect can easily multiply the direct impact of a leverage shock by 5 times.

Our set up allows us to study some of the implications of volatility feedback of which we find some supporting evidence. Lagged volatility does have a positive effect on

[2] The unbalanced structure of the dataset mitigates any potential sample selection biases.

the risk premium. However, we find a small but significant negative contemporaneous correlation between the risk premium and the volatility. In addition, the effects present in the lags does not accumulate over time in the way that the effect of financial leverage does.

In summary, we feel that our study provides strong evidence in support of the financial leverage effect on equity volatility, strengthening the conclusions of Christie (1982). The accumulation of the leverage effect over time renders it at least up to five times larger than previously thought.

The paper is organized as follows. Section II delineates the benchmark dynamic model of leverage and volatility, addressing also the data used and the estimation methodology. Section III consider the augmented model which allows for the volatility feedback effect. In section IV, we discuss the core results of our study, extended in section V to consider impulse response functions. Section VI concludes.

I. The Benchmark Model

We consider a fixed effects panel vector autoregression (PVAR) model. The advantages of using panel data are discussed in Hsiao (2003) and the references cited therein. One advantage of particular relevance to our model is the fixed effects specification, which allows for different intercept parameters across firms. This is crucial to capture or control firm level heterogeneity and possible model misspecification, both of which are contained in the intercept. The pooled least square estimates in Christie (1983) may have heterogeneity bias in the slope estimate in the presence of heterogeneous intercepts, which is a standard result in the panel data literature, see Hsiao (2003). The estimation and inference in PVAR was first introduced in Holtz-Eakin, Newey, and Rosen (1988) cite, where the time series are assumed to be stationary and instrumental variable estimator is used. Binder et al. develop a quasi maximum likelihood (QML) estimation approach that allows for unit root processes. In our case the panel time dimension is not short and therefore we adapt their method as follows.

Let w_{it} be a $m(=2) \times 1$ vector time series which starts from time 0,

$$w_{it} = \begin{pmatrix} QR_{it} \\ \sigma_{it} \end{pmatrix} \; i = 1, \cdots, N \text{ and } t = 0, 1, \cdots, T,$$

where QR_{it} and σ_{it} are leverage ratio and realized volatility, respectively.

Consider the following fixed-effects Panel VAR model:

$$\underset{2\times1}{w_{i,t}} = \underset{2\times1}{a_i} + \underset{2\times2}{\Phi}\underset{2\times1}{w_{i,t-1}} + \underset{2\times1}{\varepsilon_{i,t}}, \tag{1}$$

where

$$a_i = \begin{pmatrix} a_{i1} \\ a_{i2} \end{pmatrix}, \ \Phi = \begin{pmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{pmatrix} \text{ and } \varepsilon_{it} = \begin{pmatrix} \varepsilon_{it1} \\ \varepsilon_{it2} \end{pmatrix}.$$

We further assume

$$\varepsilon_{i,t} \overset{i.i.d.}{\backsim} (0, \Omega_\varepsilon),$$

where

$$\Omega_\varepsilon = \begin{pmatrix} \sigma_{\varepsilon 11} & \sigma_{\varepsilon 12} \\ \sigma_{\varepsilon 21} & \sigma_{\varepsilon 22} \end{pmatrix}$$

with $\sigma_{\varepsilon 12} = \sigma_{\varepsilon 21}$.

By taking the first difference of (1), we eliminate the fixed effects a_i and obtain

$$\Delta w_{i,t} = \Phi \Delta w_{i,t-1} + \Delta \varepsilon_{i,t}, \tag{2}$$

where $\Delta w_{i,t} = w_{i,t} - w_{i,t-1}$ and $\Delta \varepsilon_{i,t} = \varepsilon_{i,t} - \varepsilon_{i,t-1}$. Define

$$\Delta \eta_i = \begin{pmatrix} \Delta w_{i2} - \Phi \Delta w_{i1} \\ \vdots \\ \Delta w_{iT} - \Phi \Delta w_{i,T-1} \end{pmatrix}_{m(T-1)\times 1}$$

and the variance-covariance matrix of $\Delta \eta_i$ is given by

$$\Sigma_{\Delta\eta} = \begin{pmatrix} 2\Omega_\varepsilon & -\Omega_\varepsilon & & & 0 \\ -\Omega_\varepsilon & 2\Omega_\varepsilon & -\Omega_\varepsilon & & \\ & -\Omega_\varepsilon & \ddots & & \\ & & & 2\Omega_\varepsilon & -\Omega_\varepsilon \\ 0 & & & -\Omega_\varepsilon & 2\Omega_\varepsilon \end{pmatrix}.$$

Finally, define the parameter vector $\theta = (\phi_{11}, \phi_{12}, \phi_{21}, \phi_{22}, \sigma_{\varepsilon 11}, \sigma_{\varepsilon 12}, \sigma_{\varepsilon 22})'$.

The log likelihood function for firm i is given by

$$l_i(\theta) = -\frac{m(T-1)}{2}\log(2\pi) - \frac{1}{2}\log|\Sigma_{\Delta\eta}| - \frac{1}{2}\Delta\eta_i'\Sigma_{\Delta\eta}^{-1}\Delta\eta_i$$

The log likelihood function for all the firms is

$$l(\theta) = -\frac{mN(T-1)}{2}\log(2\pi) - \frac{N}{2}\log|\Sigma_{\Delta\eta}| - \frac{1}{2}\sum_{i=1}^{N}\Delta\eta_i'\Sigma_{\Delta\eta}^{-1}\Delta\eta_i \tag{3}$$

The objective is

$$\max_{\theta}\ l(\theta)$$

while ensuring a positive definite $\hat{\Omega}_\varepsilon$.

In order to ensure a positive definite $\hat{\Omega}_\varepsilon$, we reparameterize Ω_ε as

$$\Omega_\varepsilon = \begin{pmatrix} \omega_{11}^2 & \omega_{11}\omega_{12} \\ \omega_{11}\omega_{12} & \omega_{11}^2 + \omega_{22}^2 \end{pmatrix},$$

and our parameter vector becomes $\theta = (\phi_{11}, \phi_{12}, \phi_{21}, \phi_{22}, \omega_{11}, \omega_{12}, \omega_{22})'$.

The quasi MLE (QML) has asymptotic normal distribution

$$\sqrt{N}\left(\hat{\theta} - \theta\right) \backsim N(0, V_{QML}),$$

where

$$V_{QML} = H^{-1}GH^{-1} \tag{4}$$

with

$$H = E\left[-\frac{1}{N}\frac{\partial^2 l(\theta)}{\partial\theta\partial\theta'}\right],$$

$$G = E\left[\frac{1}{N}\frac{\partial l(\theta)}{\partial\theta}\frac{\partial l(\theta)'}{\partial\theta}\right].$$

In practice, we have

$$\hat{H} = -\frac{1}{N} \cdot \frac{1}{N} \sum_{i=1}^{N} \frac{\partial^2 l_i(\theta)}{\partial\theta\partial\theta'}|_{\theta=\hat{\theta}}$$

$$\hat{G} = \frac{1}{N} \cdot \frac{1}{N} \sum_{i=1}^{N} \left(\frac{\partial l_i(\theta)}{\partial\theta}_{|\theta=\hat{\theta}} \cdot \frac{\partial l_i(\theta)'}{\partial\theta}_{|\theta=\hat{\theta}} \right).$$

The second equation in the PVAR model (1) gives the dynamic relationship between volatility and leverage ratio:

$$\sigma_{it} = a_{i2} + \phi_{21} QR_{i,t-1} + \phi_{22}\sigma_{i,t-1} + \varepsilon_{it2}.$$

The results in the table are obtained from the following differenced model. We focus first on the parameter ϕ_{21}.

$$\Delta\sigma_{it} = \phi_{21}\Delta QR_{i,t-1} + \phi_{22}\Delta\sigma_{i,t-1} + \Delta\varepsilon_{it2}$$

II. Time varying risk premium and leverage

French, Schwert Stambaugh (1987), Campbell and Hentschel (1992), and more recently Bekaert and Wu (2000) point out that time varying risk premium could be the reason for asymmetric volatility, rather than the firms' leverage. The varying risk premium hypothesis suggests that if volatility is priced, an anticipated increase in volatility raises the required return on equity, leading to an immediate stock price decline. This hypothesis applies directly to the market portfolio. For individual firms in a CAPM set up, the relevant measure of risk is instead the covariance of the stock with the market portfolio. The relationship in this case is indirect. In particular, the time-varying risk premium theory can contribute to explain firm-specific volatility asymmetry, through changes in the covariances with the market determined by changes in conditional volatility. The relationship between covariance risk and stock and market conditional volatility, and correlation can be better understood by rewriting the conditional covariance as

$$Cov_{t-1}(r_{i,t}, r_{m,t}) \equiv \rho_{jm,t-1}\sigma_{i,t-1}\sigma_{m,t-1}, \tag{5}$$

where $\rho_{im,t}$ is the conditional correlation between market and firm i, $\sigma_{i,t}$ is the conditional volatility of the firms stock and $\sigma_{m,t}$ is market conditional volatility. The identity (5) serves to illustrate that the relationship between covariance and stock and market volatility depends on the sign of the correlation $\rho_{im,t}$, and the magnitude of $\rho_{im,t}$, $\sigma_{i,t}$ and $\sigma_{m,t}$. More precisely

$$\frac{\partial Cov_{t-1}(r_{i,t}, r_{m,t})}{\partial \sigma_{i,t}} = \rho_{im,t-1}\sigma_{m,t-1} \tag{6}$$

and hence, *ceteris paribus*, the individual stock risk premium should respond positively to increases in stock volatility only if stock return is positively correlated with the market return.

Equation (1) provides a system that can be thought as a dynamic version of Christies (1983) model. However, the most recent literature cited above shows that time varying risk premia are a viable explanation of volatility asymmetry. Our goal in what follows is to allow volatility to depend on a measure of the time-varying risk premium and verify whether the importance of the leverage variable QR_t in explaining firm volatility decreases.

Therefore, we assume that investors require returns consistently with the conditional CAPM. In particular, the conditional CAPM implies that

$$E_{t-1}[r_{i,t}] = \frac{E_{t-1}[r_{m,t}]}{Var_{t-1}[r_{m,t}]} Cov_{t-1}[r_{i,t}, r_{m,t}] \tag{7}$$

where $r_{i,t}$ and $r_{m,t}$ are the returns in excess of the T-Bill of asset i and the market, respectively, and E_t denotes the expectation operator conditional on the available information set. We take as an approximated measure of the quarterly required returns the realized expected returns computed using the daily data.

$$\overline{r}_{i,t-1} \equiv E_{t-1}[r_{i,t}] = \frac{\sum_{h=1}^{Q} r_{m,t-1,h}}{\sum_{h=1}^{Q} r_{m,t-1,h}^2} \sum_{h=1}^{Q} [r_{i,t-1,h} r_{m,t-1,h}] \tag{8}$$

where Q is the number of days in each particular quarter. The returns variable $\overline{r}_{i,t}$ is essentially an ex post measure of the required return based on the conditional CAMP. The advantage of this measure is that is does not need any estimation procedure *per se* as is based on realized variance and covariance (see e.g. Andersen Bollerslev (1998), Andersen et al. (2001, 2002, 2003)). Another desirable feature of this implementation of the conditional CAPM is that the variation in the risk premium can be driven by the time variability of any of its three components, namely variance, covariance and excess market return. In other words, (8) it encompasses both the parametrization of the conditional CAMP with time varying beta and that with a time varying price of market risk. We test this implementation of the conditional CAPM by regressing the market returns on the expected returns computed from (8) as follows.

$$r_{i,t} = \alpha + \beta \overline{r}_{i,t} + \varepsilon_{i,t}$$

Under the null that $\overline{r}_{i,t}$ is a suitable proxy of the risk premium, α should be 0 and β should be 1. We find that α is quite small at $-.0221$, although significantly different from 0[3]. As one may expect, this suggests that $\overline{r}_{i,t}$, may not capture all the risk factors that drive the variation in $r_{i,t}$. At the same time, the coefficient β is significantly different from 1 at 1.196, indicating that $\overline{r}_{i,t}$ is possibly a downward biased measure of the required returns. These results in turn suggests that the coefficients that we estimate for $\overline{r}_{i,t}$ in the panel VAR system shown in the following section are possibly upwardly (in absolute terms) biased estimators of the true coefficients. The R^2 of the regression is 0.1242 showing some non negligible predicting power. Similar results hold for the four different quantiles.

These results jointly suggest that $\overline{r}_{i,t}$ may be considered an acceptable approximation of the the risk premium commanded by the stocks we consider for the purpose of this study.

With these caveats with regard to the definition of the risk premium variable, we then define an augmented VAR equation as follows

Let w_{it} be a $m(=3) \times 1$ vector time series which starts from time 0,

$$w_{it} = \begin{pmatrix} QR_{it} \\ \sigma_{it} \\ \overline{r}_{it} \end{pmatrix} \quad i = 1, \cdots, N \text{ and } t = 0, 1, \cdots, T,$$

where QR_{it} and σ_{it}, and $\overline{r}_{i,t}$, are the leverage ratio, the realized volatility, and stock i risk premium, respectively.

The the augmented model is then

[3]We correct for heteroschedasticity and autocorrelation using bootstrap standard errors with 50 replications.

$$\Delta w_{i,t} = \Phi \Delta w_{i,t-1} + \Delta \varepsilon_{i,t} \tag{9}$$

where $\Delta w_{i,t} = w_{i,t} - w_{i,t-1}$ and $\Delta\varepsilon_{i,t} = \varepsilon_{i,t} - \varepsilon_{i,t-1}$.

In a more explicit form we have

$$\begin{aligned}
\Delta QR_{i,t} &= \phi_{11}\Delta QR_{i,t-1} + \phi_{12}\Delta\sigma_{i,t-1} + \phi_{13}\Delta\overline{r}_{i,t-1} + \Delta\varepsilon_{it1} \\
\Delta\sigma_{it} &= \phi_{21}\Delta QR_{i,t-1} + \phi_{22}\Delta\sigma_{i,t-1} + \phi_{23}\Delta\overline{r}_{i,t-1} + \Delta\varepsilon_{it2} \\
\Delta\overline{r}_{i,t} &= \phi_{31}\Delta QR_{i,t-1} + \phi_{32}\Delta\sigma_{i,t-1} + \phi_{33}\Delta\overline{r}_{i,t-1} + \Delta\varepsilon_{it3}
\end{aligned} \tag{10}$$

with

$$\Omega_\varepsilon = \begin{pmatrix} \sigma_{\varepsilon 11} & \sigma_{\varepsilon 21} & \sigma_{\varepsilon 31} \\ \sigma_{\varepsilon 21} & \sigma_{\varepsilon 22} & \sigma_{\varepsilon 32} \\ \sigma_{\varepsilon 31} & \sigma_{\varepsilon 32} & \sigma_{\varepsilon 33} \end{pmatrix}$$

In order to ensure a positive definite $\hat{\Omega}_\varepsilon$ estimate, we reparameterize Ω_ε as.

$$\Omega_\varepsilon = \begin{pmatrix} \omega_{11}^2 & \omega_{11}\omega_{21} & \omega_{11}\omega_{31} \\ \omega_{11}\omega_{21} & \omega_{11}^2 + \omega_{22}^2 & \omega_{21}\omega_{31} + \omega_{22}\omega_{32} \\ \omega_{11}\omega_{31} & \omega_{21}\omega_{31} + \omega_{22}\omega_{32} & \omega_{11}^2 + \omega_{22}^2 + \omega_{33}^2 \end{pmatrix}.$$

The parameters vector is now θ
$(\phi_{11}, \phi_{12}, \phi_{1,3}, \phi_{21}, \phi_{22}, \phi_{2,3}, \phi_{3,2}, \phi_{3,1}, \phi_{3,3}, \omega_{11}, \omega_{21}, \omega_{31}, \omega_{22}, \omega_{32}, \omega_{33})'$

III. The Data

The data are from the CRSP quarterly database and COMPUSTAT daily database merged using the identifiers CUSIP, and CNUM. We use only one class of stock for each firm, the one for which the CUSIP's last two digits are 10. The sample period starts the first quarter of 1971 and ends the fourth quarter of 2005. The quarterly volatilities σ_{it} are realized volatilities computed from the daily log returns. We use the Fama and French industry classification and drop the firms classified as financials, banks, and other. The debt is computed as the sum of total liabilities (data54) and preferred stock (data55).

The value of equity is computed as the product of common shares outstanding (data61) and price at the end of the quarter (data14). The leverage variable $QR_{i,t}$ is then defined as the ratio of debt over equity at time t for firm i. Table I presents the descriptive statistics of the entire dataset and for the four quartiles. Quartiles are obtained based on the average $QR_{i,t}$. Notice the high skewness of the leverage ratio due to some extremely high leverage.

Panel 2 shows the same statistics for the dataset after eliminating the firms that have a leverage ratio QR above one hundred at any point in time. The reason we eliminate these outliers is twofold. Firstly, they have an undue influence on the estimation procedure. Secondly, from the inspection of the data we gather that the cause of the high leverage ratio is typically the extremely low equity, which in turn is suggestive of potential distress. Under such circumstances, the assumption that debt is going to be repaid at face value is no longer valid. Hence the book value of debt could not be used as a measure of debt's value.

The resulting quarterly time series for each firm have in general different starting date and length, which is important to avoid the sample selection bias. In other words, any attempt to obtain balanced dataset by choosing a subperiod and a subset of firms for which the data are available in that period may introduce sample selection bias. Using the entire universe of CRISP/COMPUSTAT firms mitigates this concern. Our results are obtained using the dataset without outliers.

Figure 1 shows the time series of the cross sectional averages of the leverage variable for each quarter, with one standard deviation bands. The variability of the cross sectional distribution of the first two sample moments appears related to the business cycles. We notice that when the average leverage level increases also the spread around the mean increases. The figure also shows how the cross sectional variance increases with the quartile.

Figure 2 similarly represents the realized volatility variable. We notice that when average volatility increases, also variance of realized volatility increases. We also note that this figure may not be as informative as the Figure 1 as firms are assigned to quartile by leverage, not realized volatility. Similarly, the plot of the expected return variable does not appear to be informative and is omitted to conserve space.

IV. Empirical Results

Following Christie (1982) we partition the dataset on the basis of the average leverage. Each firm is assigned to a quartile increasing in leverage. We report estimates for the four quartiles and for the entire sample. This means that the firms in Q4 are those for which the average level of QR is the highest during their respective sample period.

We estimate the model by QML. We maximize the likelihood function in (3) using a hill-climbing algorithm that is robust to local optima using at least three arrays of at randomly selected starting values. All different starting values attain the same maximized likelihood value up to the third decimal. We present the parameters that maximize the likelihood.

The robust standard errors are computed using numerical gradient and Hessian. Specification tests of the model reveal that the VAR(1) structure is able to capture most of the dynamics of the original data series. Less parsimoniuos specifications, including a PVARMA(1,1) model did improve model fit.

One important property of the QML estimation the VAR(1) model is that parameters estimates are robust to heteroskedasticity and serial correlation in the error term. As well, robust variance covariance estimate V_{QML} is used for inference.

Whitelaw (1994) and Brandt and Kang (2004) use VAR to study the dynamic relationship between volatility and expected returns at the market level. We are first to our knowledge to take into consideration the dynamic interrelation of volatility, leverage, and expected return at the firm level using panel data. Using VAR is important for our purpose as the dynamic setting can both shed some light on how the leverage effect and the feedback effect interrelate simultaneously, and how their relationship unfolds over time. On the one hand, the model allows the estimation of the covariance matrix of the error differences, which captures the contemporaneous correlation among the shocks to variables. On the other hand, looking at the estimated coefficients illustrates whether these relationships cumulatively reinforce each other or rather tend to offset each other over time. In the following section we examine these relationships. In addition, the panel data methodology takes care of the possible heterogeneity among firms and increases the estimation efficiency due to the large sample size.

In the following section we present the results of both the benchmark model and the augmented model.

A. Dynamic effects

Table VI shows the parameter estimated for the restricted model.[4] This table corresponds to table 2 in Christie (1982). As the comparison of table VI and VII shows, results from the benchmark model and the augmented model are strikingly similar. We therefore discuss only the results in table VII. We examine the parameters related to leverage effect first, then those related to feedback, and the remaining ones last.

The results in table VII shows a large increase in the importance of firm leverage to explain individual stock volatility as compared with the results in Christie (1983).

The coefficient $\phi_{1,1}$ captures the relationship between leverage and its own lag. Unsuprisingly, leverage is highly persistent, with highly significant values across the quartiles ranging between 0.83 for Q2 and 0.89 for the entire sample.

The coefficient $\phi_{1,2}$ is positive for all quantiles. The sign is in agreement with the volatility feedback story. If firm level volatility increases, i.e., $\triangle\sigma_{i,t-1} > 0$, then according to volatility feedback story, *ceteris paribus*, higher volatility raises the required rate of return on equity, which causes an decline in stock price. The decline in stock price increases leverage, thus $\phi_{1,2}$ should be positive.

Consistently with equation (5) in Christie (1982), the coefficient $\phi_{1,2}$ also shows an increasing patterns as leverage ratio increases. In the equation

$$\sigma_s = \sigma_V + \sigma_V \left(1 - 2h\right) LR,$$

where σ_s, σ_V and LR are equity volatility, firm market value volatility (assumed to be constant) and leverage ratio, respectively h is an increasing function of LR.

The above equation says $\sigma_V \left(1 - 2h\right)$, which is equal to our ϕ_{21} in VII, is a decreasing function of LR. If we rewrite the above function as follows

$$LR = \frac{-1}{1 - 2h} + \frac{1}{\sigma_V \left(1 - 2h\right)} \sigma_s,$$

it is clear that the coefficient $\frac{1}{\sigma_V(1-2h)}$ should be an increasing function of LR. In a dynamic model, the estimate of $\frac{1}{\sigma_V(1-2h)}$ is the coefficient $\phi_{1,2}$ and QR is the empirical counterpart to LR. This explains the increasing pattern of ϕ_{12} in $QR's$ quartile.

The dependece of the $\phi_{1,2}$ and $\phi_{2,1}$ on firm leverage implies slope heterogeity in the

[4] We cannot directly compare our results to Christie's because the sample period and data are different and we have no way retrieve his original data.

PVAR model, i.e. $\phi_{1,2}$, $\phi_{2,1}$ take different values for different firms with different leverage ratios. However, it can be shown that these coefficients can be seen as a random variables with $\phi_i = \bar{\phi} + e_i$ where e_i is a zero mean process. The QMLE procedure insures that $\phi_{1,2}$, $\phi_{2,1}$ are consistent.[5]

The coefficient $\phi_{2,1}$ captures the relationship between volatility and lag leverage. Its magnitude varies between 0.129, and 0.013. The sign is positive and the parameters are significant for all quartiles and for the entire sample. The magnitude it is decreasing in leverage. This means that the financial leverage of firms with high QR are less sensitive to shocks to firm volatility than that of firms with low QR. Our results confirm Christie's that the rate at which the leverage affects volatility declines as financial leverage increases. However, the magnitude of the coefficient we estimate is much larger than that estimated by Christie: for the Q1 is about 19 times, for Q2 about 17 times, for Q3 is 19 times, for Q4 is about 7 times, and for the entire sample is about 5 times as large. In other words, our findings strengthen Christie's conclusion that financial leverage is an important determinant of the volatility dynamics. In other words, our findings strengthen Christie's conclusion that financial leverage is an important determinant of the volatility dynamics.

Brandt and Kang (2004) point out that one important aspect of using a dynamic model is that, depending on the sign of the coefficients, shocks to one variable may continue to affect all variables in the system to a different extent over a long period. In all the quartiles both $\phi_{1,2}$, and $\phi_{2,1}$ are positive and significant. This means that, *ceteris paribus*, a shock to either volatility or leverage will accumulate over time at a rate that depends on these two coefficients. This modeling feature sets our study aside from the extant literature. In fact, however small the effect of a change in leverage on volatility may seem by only looking at the first lag, when both the positive effects of lag volatility on leverage, and of lag leverage on volatility are taken into account, the cumulative effect of a shock to leverage on volatility becomes substantial. In the context of the augmented model, this result is illustrated through the plots of the cumulative impulse response functions in Figure 3. Figure 3 shows the cumulative effect of one orthogonalized standard deviation shock from QR to σ. The horizontal axis measures the quarters and the vertical axis is expressed in percentage annualized volatility. The

[5] See Corollary 5.3 in White (1994)

figure suggests that in all quartiles one standard deviation shock to QR on σ cumulates over the following 12 quarters to roughly six or seven times the effect observed after the first quarter. In addition, the same figure shows that whereas one standard deviation shock to QR on σ for firm in quartile one increases volatility of about 12 per cent over the next 12 quarters, for a firm in quartile four the increase is about 50 per cent annualized volatility over the next 12 quarters. This emphasizes the merit of using a VAR system to uncover the leverage effect over time, which is not discussed in the extant literature.

The coefficient $\phi_{3,1}$ captures the relationship between financial leverage and lag required returns. It is positive and significant, for the Q3, Q4, and for all sample. This means than an increase in leverage is followed by a higher required returns. The fact that this relationship is significant only for the firms with higher leverage ratio suggests that the market requires a compensation only when a firm's leverage increases from a relatively high level to an even higher level, and hence increases default risk.

The coefficient $\phi_{3,2}$ captures the feedback effect at the one lag frequency. This positive sign is consistent with the feedback story as it shows that an increase in volatility is followed by an increase in expected returns. However, when this positive coefficient is considered jointly with the negative or mostly insignificant estimates of $\phi_{2,3}$ it appears that the lag structure of the VAR system dampens the effects of shocks to expected return and to volatility. As a consequence, the positive relationship does not accumulate and it dies out quickly. This is the second important finding of our paper that highlights the importance of using a dynamic system.

Figure 4 illustrates this point. It shows the cumulative effect of one orthogonal shock from σ to $\overline{r}$. The horizontal axis measures the quarters and the vertical axis is expressed in percentage annualized require excess return. The figure suggests that in all quartiles one standard deviation shock to from σ to $\overline{r}$ cumulates over the following 12 quarters. The cumulated effect on $\overline{r}$ from shocks to σ varies from 6 to 25 basis points over the next 12 quarters depending on the quartile. However, by comparing Figure 3 to Figure 4 it is apparent that the cumulated effect of such a shock is much smaller than for the case of a shock to the leverage variable QR. In other words, the effect on σ from shocks to QR and the effect on $\overline{r}$ from shocks to σ are both significant at the one lag frequency. However, the dynamic structure of the system is such that over time the leverage effect cumulates more than the volatility feedback effect.

Own lag of volatility, as measured by the coefficient $\phi_{2,2}$ has a positive and fairly large effect on current volatility. This effect is documented in the large literature on

GARCH and increases as leverage increases. The magnitude of the coefficients should be interpreted while keeping into account the quarterly data frequency.

[Table VI about here]

The parameter $\phi_{1,3}$, captures the effect of lag required returns on financial leverage. This coefficient is negative, but insignificant for all the quartiles. However it is negative and highly significant for the entire sample. This negative relationship is consistent with the notion that when a firm experiences a decrease in the cost of capital, it also finds raising capital in the form of debt easier, and it may prefer the second alternative. The parameter $\phi_{3,1}$ is positive and significant for the entire data set. This is consistent with the fact already discussed above that when QR increases, also σ increases, and hence the required return must increase to compensate for the greater risk.

Finally, $\bar{r}$ has a negative correlation with its own lag. The overall low statistical significance of the parameters in the third equation may be suggestive that model augmented to include the risk premium variable may add little information. This not however the case. The Wald test in table IX rejects the hypothesis that the parameters $\phi_{1,3}, \phi_{2,3}, \phi_{3,1}, \phi_{3,2}, \phi_{3,3}$ are jointly zero, providing support for the augmented model. This finding is consistent with the recent literature highlighting the presence of the time varying risk premium to explain volatility asymmetry.

B. Contemporaneous correlation

In addition to the intertemporal effects, the VAR system allows to make inferences about the contemporaneous correlation among the variables. Table VIII shows the contemporaneous correlation between the shocks to changes in leverage, volatility, and required returns estimated from the trivariate PVAR system covariance matrix.[6] The robust t-stats are computed using the delta method. In the context of our study, since we are using quarterly data, contemporaneous should be interpreted as "same quarter", rather than "instantaneous".

The correlations between shocks are all significant at any conventional level. The contemporaneous correlation between the shocks to changes in QR and σ is positive. This means that when volatility increases, *ceteris paribus,* either debt increases, or equity

[6] The correlation matrix is simply computed from the estimated variance covariance as $[diag(\Omega_\varepsilon)]^{-1/2}\,\Omega_\varepsilon\,[diag(\Omega_\varepsilon)]^{-1/2}$, where $diag(\Omega_\varepsilon)$ is the matrix with the same main diagonal as Ω_ε and zero elsewhere.

declines, or both. This result is supportive of a contemporaneous financial leverage effect. In fact, it characterizes one possible definition of the leverage effect. This correlation increases from 5.6 per cent for the firms in the first quartile to 13.2 per cent for the firms in the fourth quartile. It also is more pronounced for firms that are highly levered.

The contemporaneous correlation between the shocks to changes in $\bar{r}$ and σ is negative. It varies between -7.1 per cent for the first quartile to -9.8 per cent for the fourth quartile. This result is at odds with a contemporaneous feedback effect at the firm level. To observe the feedback effect this correlation should be positive. It is however consistent with the results in Brandt and Kang (2004) which study the same relationship at the market level. Note that this result is not in contrast with a positive relationship between risk and expected return. In fact in this framework not volatility, but covariance with the market return is the appropriate measure of risk at the firm level. This result may be due to the fact that expected returns move sluggishly with respect to firm volatility and leverage.

The contemporaneous correlation between required returns and leverage is negative. This may seem puzzling if one considers leverage as one measure of firm riskiness. However, even if there is not contemporaneous positive relationship between leverage and the remuneration required by investor to hold that risk, the sign turns positive on the first lag as shown by the coefficient $\phi_{3,1}$.

In summary, when we compare the evidence in favor of either leverage on feedback,we find that the leverage effect is large and the dynamic system shows that its importance cumulates over a substantial number of lags. On the contrary, firstly there is no contemporaneous feedback effect, secondly the lag structure is such that the feedback effect observed at one lag frequency does not cumulate over time as much. These consideration are made more vividly clear by the inspection of the impulse response function that discussed above.

[Table VIII about here]

V. Impulse Response Function

In the following section we discuss the impulse response function from the PVAR system. In the impulse response functions, all the shocks are one standard deviation and are orthogonalized. The three different shocks are from QR, σ, and $\bar{r}$, respectively. In each subplot each line represents the marginal effect of a shock to one of the three equations in the VAR system. For instance, the first subplot shows the marginal effect of a shock to QR on QR, σ, and $\overline{r}$ for firms in the first quartile. Notice that the lines in each plot are not directly comparable to each other due to different scaling an size of the shocks.

The first column of subplots shows that a shock from QR has a positive and persistent effect on all the variables for all the quantiles.

Similarly, a shock from realized volatility to the other variables has a positive effect on other variables. An increase in firm volatility has virtually no effect on a firm's leverage when leverage is low. However, when leverage ratio increases as we move from the first quartile the fourth quartile, we observe leverage ratio will first increase then decrease. In particular, for firms with high leverage ratio in quartile four, the effect of an increase in volatility is so persistent that less than half of initial effect dies out after 3 years. We note that the QR response to a shock from σ is hump shaped for the firm with high QR. In other words, the largest effect of the shock occurs after three quarters.

For the third column of subplot we note that a shock from required returns has a negative effect on all the variable with the only exception of volatility in the first quartile.

By inspecting the (red) circled line it appears that the effect of a shock for required returns on itself dissipates after one quarter. On the contrary its effect is quite persistent on σ.

VI. Conclusions

We use a Panel Vector Auto Regression model to study the dynamic relationship among financial leverage, firm equity volatility, and time varying risk premia. We use a large unbalanced panel data set during the period 1971-2005. We believe that the scale of the study to be unprecedented, particularly in the context of a dynamic econometric model.

Our model allows for dynamic endogeneity among the firm level leverage, equity volatility, and risk premium. The fixed effects model controls for firms heterogeneity. We reconfirm the relationship between equity volatility and the debt ratio presented in Christie (1982) across the four leverage quartiles.

Our main finding is that a dynamic set up is important to capture the cumulative leverage effect. The impulse response functions suggest that financial leverage is an economically more significant determinant of equity volatilities than previous work has documented, and its effect accumulates over time. The accumulation of the leverage effect over time renders it at least up to five times larger than previously thought. Our study suggests that past results may be due to not fully allowing for the endogenous nature of the relationship between capital structure and business risk.

VII. Tables and Figures

Table I
Descriptive statistics for the leverage variable QR.

Panel 1: All Sample

	Q 1	Q 2	Q 3	Q 4	All
Mean	0.184	0.540	1.315	6.984	2.315
Median	0.130	0.431	1.095	2.448	0.708
Maximum	4.264	8.882	39.678	26377.000	26377.000
Minimum	0.000	0.000	0.001	0.003	0.000
Std. Dev.	0.192	0.477	1.091	235.211	118.637
Skewness	3.912	3.546	4.715	99.435	197.145
Kurtosis	39.669	29.989	79.637	10342.310	40659.870
Jarque-Bera	1427190	1025705	7964801	1.34E+11	8.13E+12
Probability	0	0	0	0	0
Observations	24365	31613	32061	30018	118057

Panel 2: No Outliers

	Q 1	Q 2	Q 3	Q 4	All
Mean	0.182	0.533	1.288	3.739	1.483
Median	0.129	0.425	1.066	2.395	0.698
Maximum	4.264	8.882	39.678	98.387	98.387
Minimum	0.000	0.000	0.001	0.003	0.000
Std. Dev.	0.190	0.473	1.089	5.284	3.068
Skewness	3.812	3.599	4.829	6.779	10.633
Kurtosis	38.352	30.871	81.692	74.022	195.074
Jarque-Bera	1311161	1082949	8279855	6.50E+06	1.82E+08
Probability	0	0	0	0	0
Observations	24060	31367	31614	29820	116861

Table II

Descriptive statistics for the realized volatility. The annualized realized volatility is defined as $\sigma_{it} = \sqrt{4\sum_{h=1}^{Q} r_{i,t-1,h}^2}$, for all the Q days in a quarter.

No Outliers

	Q 1	Q 2	Q 3	Q 4	All
Mean	0.594	0.574	0.521	0.488	0.542
Median	0.515	0.481	0.425	0.352	0.447
Maximum	10.360	7.399	6.728	7.893	10.360
Minimum	0.000	0.000	0.000	0.000	0.000
Std. Dev.	0.375	0.380	0.409	0.450	0.408
Skewness	3.332	2.794	3.112	3.382	3.105
Kurtosis	39.915	23.590	23.750	25.274	26.442
Jarque-Bera	1410678	594877.4	618184.5	6.73E+05	2.86E+06
Probability	0	0	0	0	0
Observations	24060	31367	31614	29820	116861

Table III

Descriptive statistics for the realized annualized expected return implied by the conditional CAPM. Both variance and covariance are ex-post realized measures and are computed from daily data. The expected return variable $\overline{r}$ is defined as $\overline{r}_{i,t} = \frac{Cov_{t-1}[r_{i,t}, r_{m,t}]}{var_{t-1}(r_{m,t})} r_{m,t}$.

No Outliers

	Q 1	Q 2	Q 3	Q 4	All
Mean	0.036	0.032	0.024	0.020	0.028
Median	0.016	0.013	0.011	0.009	0.012
Maximum	5.420	7.859	7.623	4.332	7.859
Minimum	-3.544	-3.057	-4.630	-4.697	-4.697
Std. Dev.	0.381	0.346	0.312	0.280	0.329
Skewness	-0.471	-0.109	-0.136	-0.365	-0.260
Kurtosis	11.513	19.347	25.290	22.351	19.081
Jarque-Bera	73534.3	349308.4	654536.4	465905.9	1260513
Probability	0	0	0	0	0
Observations	24060	31367	31614	29820	116861

Table IV
Unconditional correlation among the variables QR, σ, and $\overline{r}$.

	Q1	Q2	Q3	Q4	All
$\rho(QR, \sigma)$	0.083	0.14	0.133	0.28	0.114
$\rho(\overline{r}, \sigma)$	-0.034	-0.04	-0.043	-0.02	-0.021
$\rho(QR, \overline{r})$	-0.070	-0.05	-0.033	-0.04	-0.046

Table V
Christie's regressions. Cross sectional averages of the parameters estimates, and t-stats of the firm-wise regressions. The time subscript for QR is consistent with Christies' description of the variable as being constructed by dividing face value of debt at the end of the previuos available data period by the value of the equity at the beginning of the period. The regression is augmented with the lag volatility to treat autocorrelation in volatility, which Christie treats before running the regression. The equation for each firm is then: $\sigma_t = \beta_0 + \beta_1 QR_{t-1} + \beta_2 \sigma_{t-1} + \varepsilon_t$

Christie - Table 2

	Q 1	Q 2	Q 3	Q 4	All
β_0	0.480	0.411	0.381	0.334	0.398
t(β_0)	**3.553**	**3.453**	**3.127**	**2.778**	**3.213**
β_1	0.192	0.069	0.039	0.019	0.074
t(β_1)	0.368	0.638	0.770	0.976	0.703
β_2	0.183	0.228	0.220	0.246	0.221
t(β_2)	1.460	1.850	1.775	1.800	1.734
R^2	0.123	0.169	0.188	0.229	0.180
β_1/β_0	0.401	0.168	0.101	0.056	0.186

Table VI

Bivariate PVAR system. Parameters estimates and robust t-stats. The parametes are the same as if the equations were expressed in levels.

$$\Delta QR_{i,t} = \phi_{11}\Delta QR_{i,t-1} + \phi_{12}\Delta\sigma_{i,t-1} + \Delta\varepsilon_{i,t1}$$
$$\Delta\sigma_{i,t} = \phi_{21}\Delta QR_{i,t-1} + \phi_{22}\Delta\sigma_{i,t-1} + \Delta\varepsilon_{i,t2}$$

Panel 1: All sample

	Q 1	t-stats	Q 2	t-stats	Q 3	t-stats	Q 4	t-stats	All	t-stats
$\phi_{1,1}$	0.8415	**51.200**	0.8343	**84.754**	0.8609	**56.728**	0.6548	**3.202**	0.6795	**7.653**
$\phi_{1,2}$	0.0111	**2.441**	0.0375	**3.845**	0.1407	**5.480**	2.7379	**3.347**	0.8965	**6.686**
$\phi_{2,1}$	0.1277	**5.248**	0.0684	**8.772**	0.0437	**11.983**	0.0052	**2.754**	0.0070	**2.566**
$\phi_{2,2}$	0.3557	**9.123**	0.3873	**19.813**	0.4139	**20.261**	0.5110	**16.832**	0.4359	**30.129**
$\omega_{1,1}$	0.1055	**22.298**	0.2758	**30.456**	0.6332	**18.157**	-237.1782	**-3.389**	119.6618	**3.393**
$\omega_{2,1}$	0.0178	**5.366**	0.0246	**6.399**	0.0241	**6.802**	0.0006	0.288	-0.0002	-0.084
$\omega_{2,2}$	-0.2931	**-27.609**	0.2881	**35.024**	0.2885	**36.426**	0.3161	**27.602**	0.2988	**62.042**

Panel 2: No outliers

	Q 1	t-stats	Q 2	t-stats	Q 3	t-stats	Q 4	t-stats	All	t-stats
$\phi_{1,1}$	0.8459	**51.542**	0.8337	**82.744**	0.8608	**55.760**	0.8832	**36.477**	0.8909	**40.273**
$\phi_{1,2}$	0.0086	**2.419**	0.0393	**3.985**	0.1381	**5.518**	0.6233	**6.136**	0.2115	**7.132**
$\phi_{2,1}$	0.1286	**5.327**	0.0697	**8.861**	0.0442	**11.818**	0.0128	**8.712**	0.0171	**11.470**
$\phi_{2,2}$	0.3534	**8.923**	0.3926	**20.103**	0.4127	**20.146**	0.4936	**16.343**	0.4256	**30.828**
$\omega_{1,1}$	0.1036	**23.161**	-0.2734	**-29.898**	-0.6352	**-18.020**	2.7935	**17.392**	-1.4606	**-18.255**
$\omega_{2,1}$	0.0162	**5.419**	-0.0249	**-6.355**	-0.0247	**-7.335**	0.0395	**7.074**	-0.0242	**-9.215**
$\omega_{2,2}$	0.2933	**27.298**	0.2872	**34.829**	-0.2915	**-36.468**	0.2974	**29.567**	0.2937	**63.783**

Table VII

Trivariate PVAR system. Parameters estimates and robust t-stats. The table shows the estimate parameters for the following system. For the covariance matrix Ω_ε, we report the coefficients of the reparameterized matrix that insure semidefinite positiveness of the variance covariance estimate.

$$\begin{aligned}\Delta QR_{i,t} &= \phi_{11}\Delta QR_{i,t-1} + \phi_{12}\Delta\sigma_{i,t-1} + \phi_{13}\Delta\overline{r}_{i,t-1} + \Delta\varepsilon_{it1}\\ \Delta\sigma_{it} &= \phi_{21}\Delta QR_{i,t-1} + \phi_{22}\Delta\sigma_{i,t-1} + \phi_{23}\Delta\overline{r}_{i,t-1} + \Delta\varepsilon_{it2}\\ \Delta\overline{r}_{i,t} &= \phi_{31}\Delta QR_{i,t-1} + \phi_{32}\Delta\sigma_{i,t-1} + \phi_{33}\Delta\overline{r}_{i,t-1} + \Delta\varepsilon_{it3}\end{aligned}$$

Trivariate Panel VAR. No outliers.

	Q 1	t-stats	Q 2	t-stats	Q 3	t-stats	Q 4	t-stats	All	t-stats
$\phi_{1,1}$	0.8459	**51.467**	0.8329	**80.647**	0.8601	**56.131**	0.8830	**36.353**	0.8909	**40.283**
$\phi_{1,2}$	0.0083	**2.355**	0.0377	**2.103**	0.1363	**4.773**	0.6157	**5.343**	0.2079	**6.074**
$\phi_{1,3}$	-0.0085	-0.881	-0.1229	-0.151	-0.2469	-1.786	-1.1362	-0.630	-0.2805	**-3.626**
$\phi_{2,1}$	0.1291	**4.060**	0.0695	**8.698**	0.0442	**11.729**	0.0127	**8.592**	0.0171	**11.666**
$\phi_{2,2}$	0.3543	**9.008**	0.3916	**20.072**	0.4126	**20.123**	0.4931	**16.526**	0.4252	**30.615**
$\phi_{2,3}$	0.0411	1.639	-0.0571	-0.372	-0.0169	**-7.544**	-0.0594	-0.163	-0.0228	-1.364
$\phi_{3,1}$	-0.0002	-0.058	0.0006	0.274	0.0013	**10.710**	0.0004	**5.612**	0.0005	**2.300**
$\phi_{3,2}$	0.0038	1.465	0.0016	0.241	0.0004	1.197	0.0052	**8.291**	0.0028	**2.548**
$\phi_{3,3}$	-0.0370	-1.144	-0.0346	-1.553	-0.0302	-1.832	-0.0276	**-5.292**	-0.0331	**-11.752**
$\omega_{1,1}$	0.1036	**23.178**	0.2732	**29.658**	0.6349	**18.133**	2.7925	**17.458**	-1.4602	**-18.263**
$\omega_{2,1}$	0.0164	**3.109**	0.0248	**3.478**	0.0246	**6.820**	0.0395	**7.144**	-0.0241	**-8.860**
$\omega_{3,1}$	-0.0068	**-15.078**	-0.0076	**-12.682**	-0.0077	**-28.542**	-0.0061	**-27.776**	0.0044	**9.429**
$\omega_{2,2}$	0.2932	**27.347**	0.2871	**34.897**	0.2916	**36.503**	0.2974	**29.726**	0.2936	**63.791**
$\omega_{3,2}$	-0.0088	**-18.398**	-0.0056	**-13.910**	-0.0033	**-16.374**	-0.0039	**-16.359**	-0.0054	**-8.351**
$\omega_{3,3}$	-0.0955	**-27.095**	0.0865	**33.287**	-0.0781	**-31.943**	-0.0697	**-30.143**	-0.0825	**-95.450**

Table VIII

Contemporaneous correlation of the shocks among the three variables QR, σ, and $\overline{r}$. The rubust t-stats are computed using the delta method.

	Q1	t-stats	Q2	t-stats	Q3	t-stats	Q4	t-stats	All	t-stats
$\rho(QR,\sigma)$	0.056	554.74	0.086	487.98	0.084	605.24	0.132	409.50	0.082	981.78
$\rho(\overline{r},\sigma)$	-0.071	-788.15	-0.088	-812.20	-0.098	-695.05	-0.087	-508.72	-0.053	-1641.44
$\rho(QR,\overline{r})$	-0.096	-733.27	-0.071	-251.86	-0.050	-195.49	-0.066	-188.75	-0.070	-1094.12

Table IX

Wald Test of linear restriction. The table shows the test that H_o: $\phi_{13}, \phi_{23}, \phi_{31}, \phi_{32}, \phi_{33}$ are jointly zero. The strong rejection of the null for all the quartiles hilights the importantce of the $\bar{r}_t$ variable to explain the dynamics of the leverage and the volatility.

Wald test of linear restriction.

Quartile	Q 1	Q 2	Q 3	Q4	All
Wald statistics	342.155	295.482	41.270	326.315	908.035
p-val	0.000	0.000	0.000	0.000	0.000

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Figure 1. Cross Sectional Average QR , with +/- One Standard Deviation Bands.

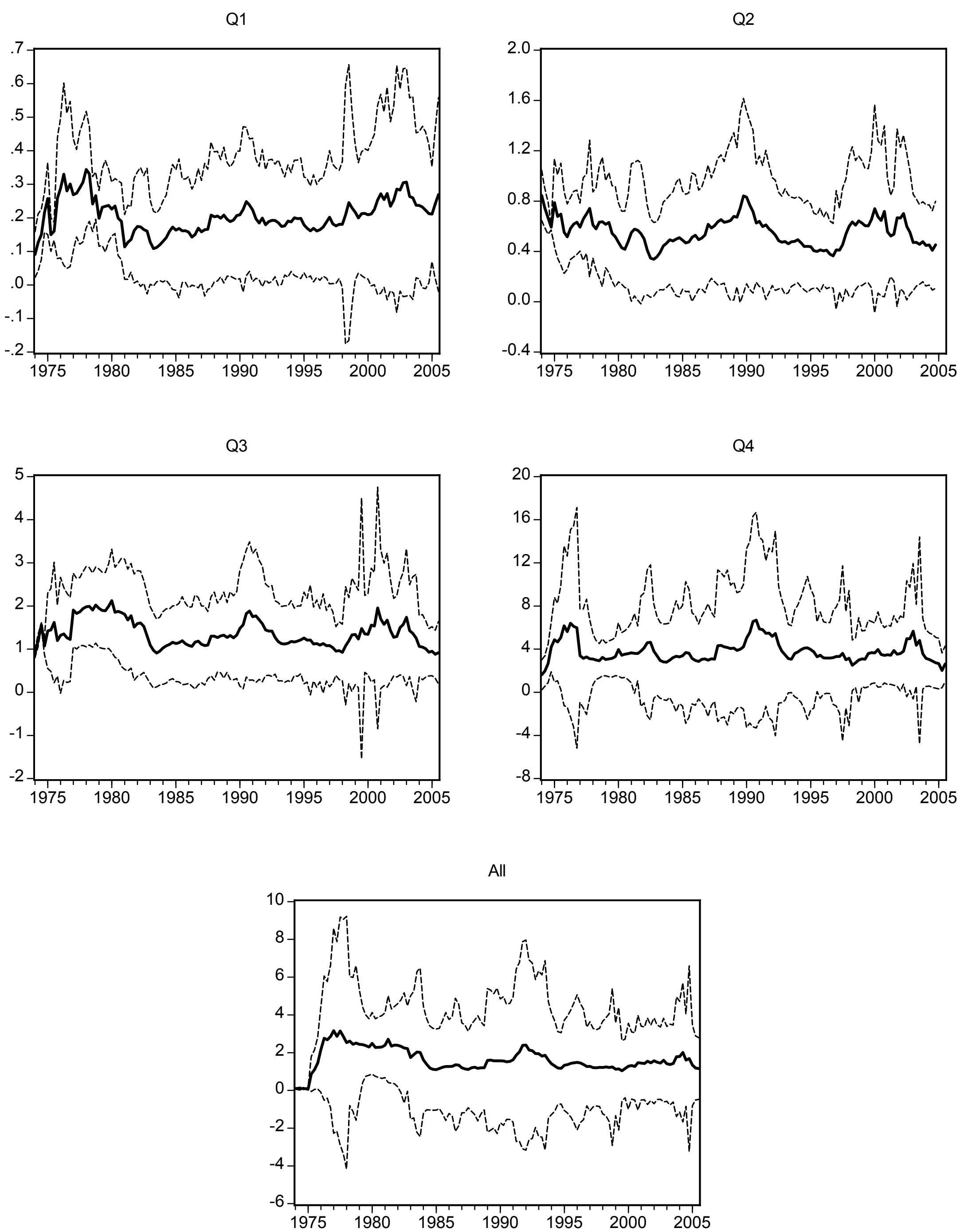


Figure 2. Cross Sectional Average Realized Volatility, with +/- One Standard Deviation Bands.

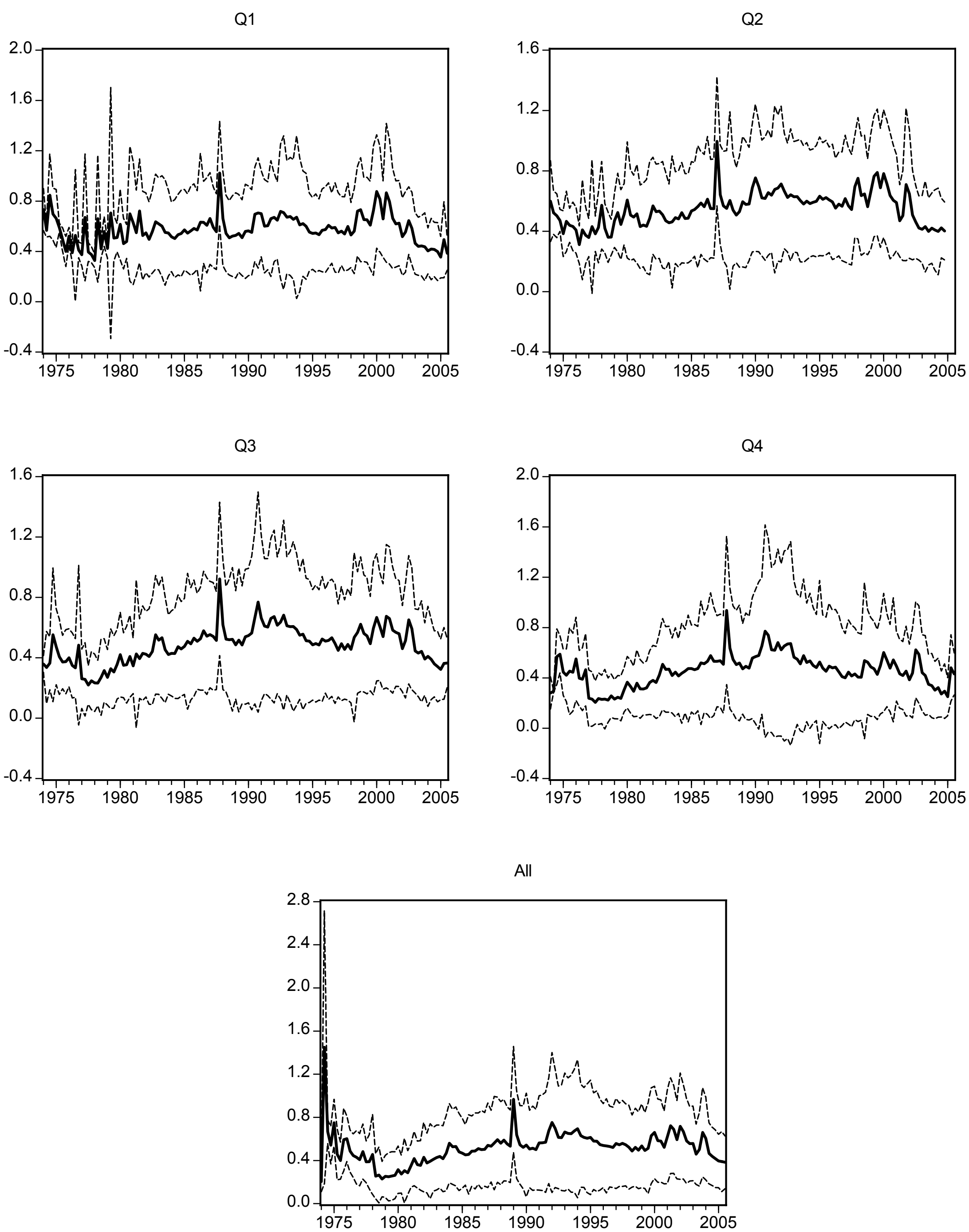


Figure 3. Cumulative Effects of an Orthogonal Shock (1 s.d. of QR) to QR on σ

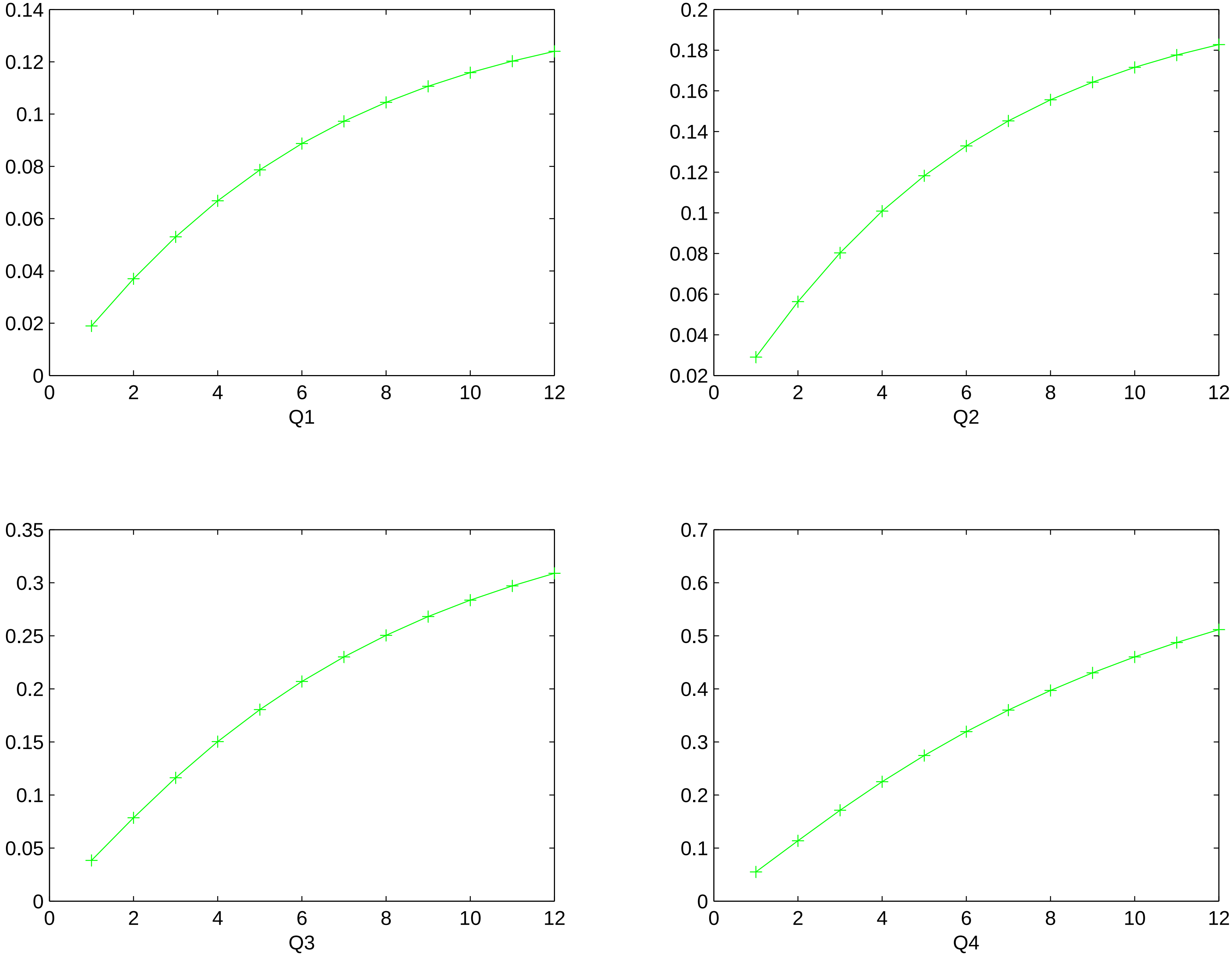
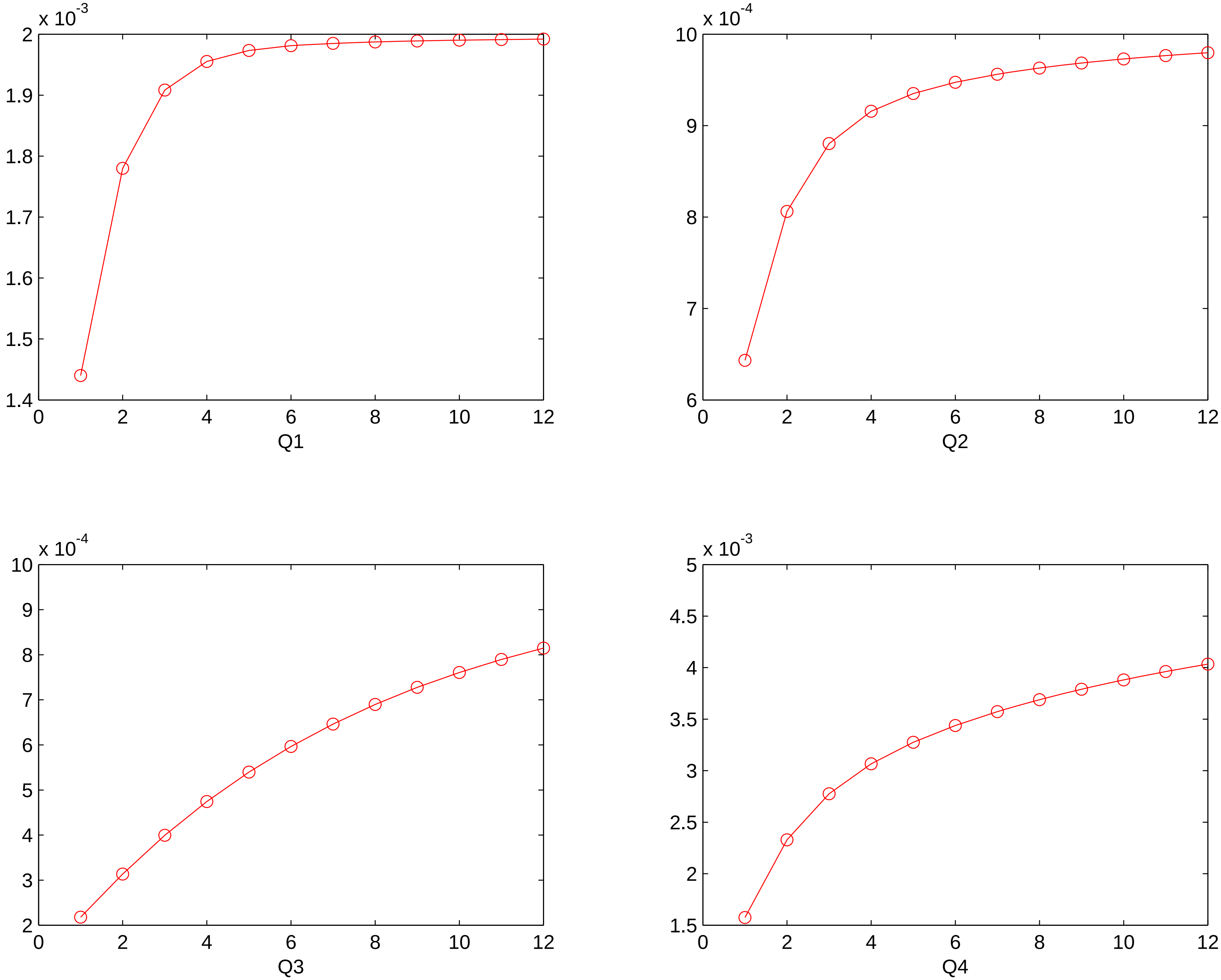


Figure 4. Cumulative Effects of an Orthogonal Shock (1 s.d. of σ) to σ on rbar



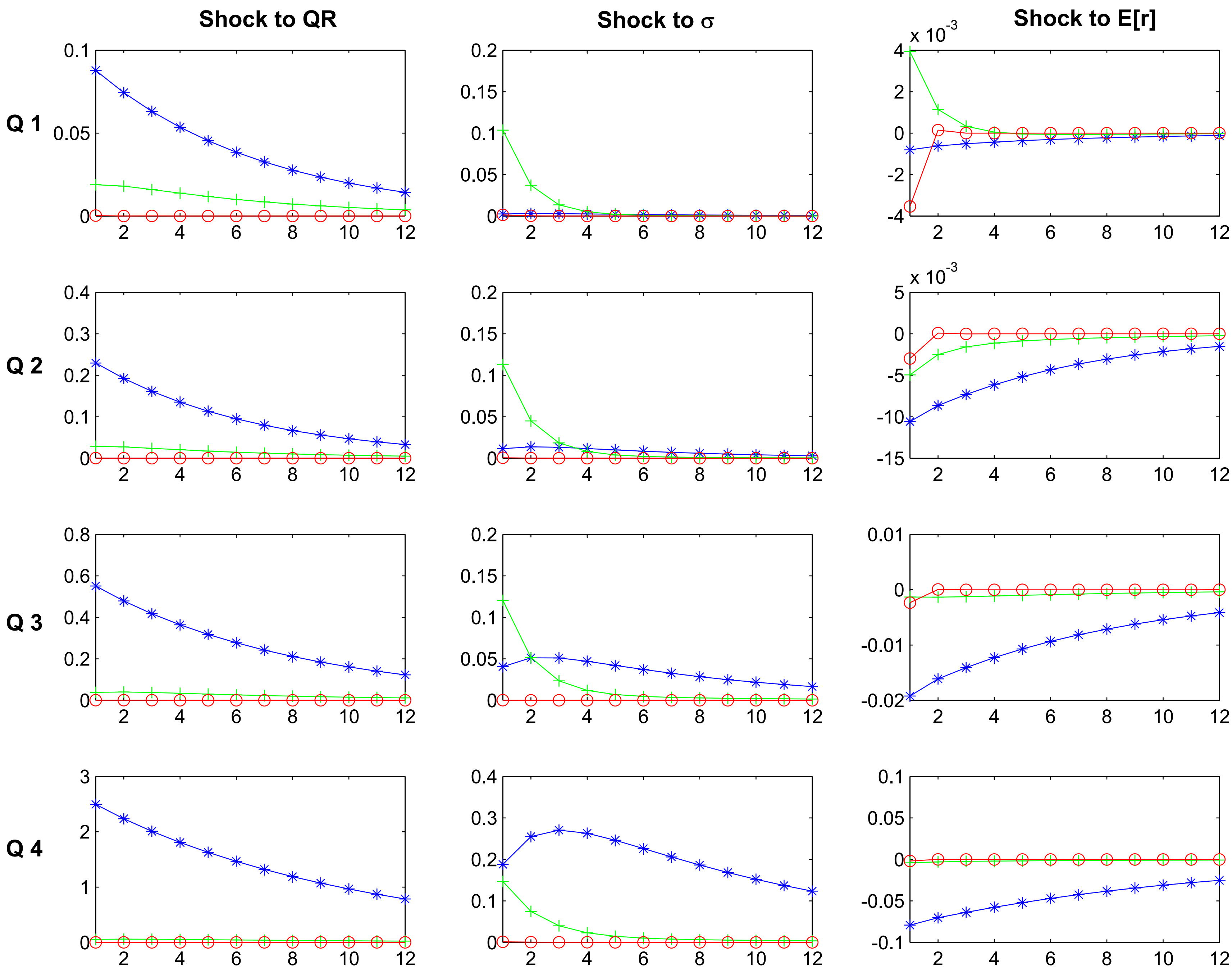


Figure 5 - Impulse response: Response to one std shock. Legend: * blue = QR; + green = σ; o red = E[r]