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An Application of the VAR Technique to a Beta Decomposition Model

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Abstract

The main purpose of this paper is to demonstrate the applicability and usefulness of the vector autoregressive (VAR) modeling technique in studying the causal linkages between a firm's degree of operating and financial leverage and its beta. In contrast to the typical correlation-based analysis used in previous research, the VAR approach can discriminate between four alternative, yet equally plausible, causal interrelationships among these variables. The empirical advantages of the VAR approach over the common correlation procedure are illustrated using data from a randomly selected company.

Introduction

Numerous studies have examined the relationship between betas of common stocks and accounting variables. For example, see Beaver, Kettler, and Scholes (1970), Gonedes (1973), Gahlon and Gentry (1982), and Mandelker and Rhee (1984). These studies, however, utilize the correlation-based approach in which beta is regressed on the contemporaneous values of the accounting variables.

This paper demonstrates the applicability and usefulness of the vector autoregressive (VAR) modeling technique to study the causal interrelationships among a firm's degrees of operating and financial leverage and its beta as embedded in the Mandelker-Rhee model. Being drawn from one firm, the empirical results are not intended to test the validity of the underlying theory. Rather, the emphasis here is primarily on showing how the VAR approach can provide more information on the relationships involved compared to the typical correlation-based analysis.

Using the VAR methodology, with data from a randomly selected company, this paper attempts:

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1. To examine if the accounting variables suggested by the Mandelker and Rhee model exert causal effects upon the systematic risk,
2. To examine if beta itself feeds back and exerts causal effects upon the accounting variables of the Mandelker and Rhee model, and,
3. To examine the causal interrelationship between the degrees of operating and financial leverage.

The first objective is similar to those in other studies cited above, but the current study uses a causality-based approach rather than a correlation-based approach. The second and third objectives were suggested by Mandelker and Rhee as interesting extensions of their study.

The Mandelker and Rhee Model

Although Hamada (1972) and Rubinstein (1973) have decomposed systematic risk into operating and financial components, it was Mandelker and Rhee (1984) who extended the model to incorporate explicitly the degrees of operating and financial leverage. Recognizing the need for a formula that would explicitly introduce the degrees of the two types of leverage, avoid econometric problems stemming from a nonlinear multiplicative effect of the financial structure on operating risk, and allow for risky debt, Mandelker and Rhee transformed the Hamada-Rubinstein decomposition formula into the following:

$$(1)\quad \beta_j = (\mathrm{DOL})\,(\mathrm{DFL})\,\mathrm{cov}\,[(\pi_{jt-1}/S_{jt-1})(\tilde{S}_{jt}/E_{jt-1}),\ \tilde{R}_{mt}]/\sigma^2_{\tilde{R}_{mt}}$$

where:

DOL = degree of operating leverage;

DFL = degree of financial leverage;

π_{jt} = earnings after interest and taxes at time t;

S_{jt} = sales at time t;

E_{jt} = market value of common equity at time t;

$\sigma^2_{\tilde{R}_{mt}}$ = variance of the rate of return on the market portfolio for the period from t-1 to t.

In other words, the systematic risk in the Mandelker and Rhee construct is a function of the firm's DOL, DFL, and the intrinsic business risk as represented by the covariance of the net profit margin at t-1 (i.e., $\tilde{\pi}_{jt}/S_{jt-1}$) and the equity turnover ratio from t-1 to t (i.e., $\tilde{S}_{jt}/E_{jt-1}$) with returns on the market portfolio. Of course, the intrinsic business risk represents the systematic risk of common stock when the firm is completely unlevered.

Mandelker and Rhee recommended that follow-up studies might take the following directions:

> . . . to introduce the intrinsic business risk of common stock into the empirical model along with DOL and DFL. Another direction is an investigation of changes over time in both DOL and DFL and the relationship between the two changes. A further investigation is warranted on changes of beta over time and corresponding changes in the degrees of operating and financial leverage. (Mandelker and Rhee, 1984, p. 56)

The current study not only addresses the above issues suggested by Mandelker and Rhee, but also applies a methodology that is appropriate in this type of research.

Data and Testing Methodology

The empirical results are based on a case study approach. Selected randomly from the companies listed on the NYSE, the company studied is Gulf States Utilities (GSU). Of course, empirical results derived from the experience of one company hardly can be generalized. Moreover, the randomly selected company is a public utility firm whose financial behavior is likely to differ from that of industrial firms. The main emphasis in this paper is not on the generalizability of the empirical results, however, but the use of the VAR technique as a better alternative to the more common but less powerful correlation-based analysis. The two approaches yield significantly different conclusions for the same company under study, as shown below.

The focus of this paper is on the four variables proposed by the Mandelker and Rhee theoretical model: beta, DOL, DFL, and the intrinsic business risk (IBR). The estimation uses annual data spanning the period 1954 through 1985. The definitions of these variables and how they were computed are explained in Table 1.

Previous empirical studies in this area are based on correlation analyses where a measure of beta is regressed on contemporaneous values of some measures of DOL and DFL, perhaps among other variables. Such a correlation-based framework, however, cannot distinguish between cause and effects. For example, Mandelker and Rhee's finding of a significant coefficient on the contemporaneous value of DOL implies four alternative hypotheses. First, it is possible that changes in DOL cause changes in beta, thus supporting the implicit hypothesis. Second, such a finding instead may imply that beta causes DOL. Clearly, a rising systematic risk potentially could induce the management to reduce the firm's operating risk. Third, it is possible that beta and DOL are causally independent. Granger (1980) has demonstrated that two variables may be highly correlated, yet not causally related. In this case, the apparent correlation between the two variables is rather elusive and simply the result of other variables causing them. The fourth hypothesis is that DOL causes beta, but with significant feedbacks (a combination of the first and second hypotheses). In this case, causality between the two variables is bidirectional. Under this scenario, most previous studies that implicitly treat DOL as an exogenous variable would suffer from simultaneous-equation bias, rendering their results both biased and inconsistent.

To summarize, there are four alternative hypotheses regarding the relationship between beta and the accounting variables such as DOL. These are that the accounting variable causes beta (the typical proposition); that beta causes the accounting variable; that beta and the accounting variable are causally independent; and that bidirectional causality exists between beta and the accounting variable. The Granger-type causality tests are a useful means to discriminate between these alternative hypotheses.

To perform these tests, the Granger definition of causality was used to estimate a 4 x 4 vector autoregressive (VAR) model. (See Hsiao (1981, 1982) and McMillin and Fackler (1984).) The variables included in the model are beta, DOL, DFL, and IBR. As mentioned above, these four variables are those proposed by the Mandelker and Rhee theoretical model.

The VAR technique recently has gained popularity. Sims (1982), for example, has recommended the VAR procedure over the more general structural modeling framework on the grounds that VAR, in contrast to the structural approach, does not impose any *a priori* restrictions on the dynamic relationships among the variables. Moreover, Webb (1984) and Lupoletti and Webb (1986) have reported empirical results showing the relative efficiency of the VAR technique over other modeling techniques. Fischer (1981, p. 402) also has argued that the VAR approach is "a convenient way of summarizing empirical regularities and perhaps suggesting predominant channels through which relations work."

Of course, the VAR methodology is not without drawbacks. The VAR approach is a reduced form technique. The implied results may not be capable of discriminating among alternative structural hypotheses. Researchers such as

Cooley and LeRoy (1985) and Leamer (1985) have criticized some common uses of the VAR technique. Nevertheless, Cooley and LeRoy (1985) and Eichenbaum (1985) have pointed out that the VAR is still a valid approach for many uses such as forecasting, the description of the cyclical behavior of a system, the generation of stylized facts about the underlying behavior of the system for the purpose of testing existing hypotheses or developing new ones, and for "determining the existence of Granger-causal orderings, even in the absence of any theoretical reason to expect them" Cooley and LeRoy (1985, p. 306). The VAR model also may be subject to the Lucas critique (Fackler (1985)). There is the possibility that a change in the underlying structure would invalidate the model inferences. Needless to say, such concern is general and not unique with VAR models. Moreover, Sims (1982) has argued that the VAR results still would be valid in the face of structural shifts provided that these shifts are not frequent or drastic.

For space considerations, full details of the VAR technique are not given. (Fackler (1985) provides a lucid account.) A few comments about the procedure as employed in this paper are worth making, however.

First, the Granger (one-sided) causality tests are selected from a number of other alternative techniques in light of the Monte Carlo evidence reported in Geweke, Meese, and Dent (1983). These Granger tests require the data to be stationary. Therefore, all variables first are transformed to covariance stationary processes. This is done by expressing the variables in logs (if only assuming positive values) and then taking their first differences. Each variable in the logarithmic first difference form is regressed against time and a constant. If the coefficient on time proves insignificant, the variable in that form is considered stationary. Otherwise a second (third, etc.) difference is used until the coefficient on time loses significance. Another requirement of the Granger test is that the stationary series have zero mean. To achieve that, each stationary series could be mean corrected either by subtracting the appropriate mean or, alternatively, by including a constant term in all regressions. The latter approach is used in this paper.

Second, rather than imposing arbitrarily a common lag length on all variables in the VAR model, the multivariate Granger causality tests are aided by Akaike's final prediction error (FPE) procedure to select the appropriate lag length for each variable. As noted by Ahking and Miller (1985), the assumption of equal lag lengths for all variables used, for example, by Lutkepohl (1982) and Plosser (1987) is too restrictive and could lead to biased results.

Third, the four equations estimated separately by the ordinary least squares (OLS) method are pooled to form a system of equations and reestimated by means of full information maximum likelihood (FIML) procedure. It should be emphasized that the system estimations incorporate the contemporaneous relationship among the variables that the single equation estimates ignore due to the sole use of lagged values of the variables. As Hsiao (1981) argues, such contemporaneous relationships could be reflected in the correlation of the error terms across equations.

Fourth, the model thus obtained is subjected to diagnostic checking by under- and overfitting the model, by testing for structural instability, and by testing for autocorrelation in the residuals. For any variable, the FPE/VAR procedure may yield three alternative outcomes. The procedure may suggest the exclusion of the variable from a given equation. As Hsiao (1981) demonstrates, such is evidence that there is no Granger-causal ordering. On the other hand, the variable instead may satisfy the FPE criterion and thus qualify to appear in the VAR final model. In this case, joint significance tests are performed on the parameters within the system estimations. If the parameters of the variable as a group fail to achieve statistical significance, the variable is said to Granger-cause the left variable only in the weak sense. If the parameters prove jointly significant, the Granger-causal ordering is said to be of the strong form.[1]

Empirical Results

This section presents and analyzes the results obtained from the VAR model. For comparison purposes, a brief discussion of some results from standard correlation-based regressions will follow.

Applying the VAR/FPE technique described in the previous section generated the following 4x4 VAR model:

$$(2) \quad \begin{bmatrix} \beta_t \\ p_t \\ f_t \\ v_t \end{bmatrix} = \begin{bmatrix} a^3_{11}(L) & 0 & 0 & a^1_{14}(L) \\ a^1_{21}(L) & a^1_{22}(L) & a^2_{23}(L) & 0 \\ 0 & 0 & a^1_{33}(L) & 0 \\ a^1_{41}(L) & 0 & 0 & a^1_{44}(L) \end{bmatrix} \begin{bmatrix} \beta_t \\ p_t \\ f_t \\ v_t \end{bmatrix} + \begin{bmatrix} c_1 \\ c_2 \\ c_3 \\ c_4 \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix}$$

where:

β_t = log beta$_t$;

[1]A maximum lag of five years is assumed. If the appropriate lag length for any variable is obtained at five years, however, the lag is extended by at least two additional years to check whether the appropriate lag is five years.

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p_t = (1-L)log DOL_t;

f_t = (1-L)log DFL_t;

v_t = (1-L)COV_t;

L = the lag operator;

a_{ij}^{k} = the k lag coefficients on variable j in equation i;

c's = constants;

u's = white noise error terms.

The specific formats of the four variables were necessitated by the stationarity requirement.

To check the adequacy of the estimated VAR system (2), the model was subjected to a series of diagnostic tests. Table 2 summarizes the results of these tests. Tests 1 through 8 ease the zero restrictions of the VAR model. Tests 9 through 16 assess whether the fit of the model could be improved by extending the existing lags (overfitting). Finally, test 17 examines whether improvement in the model could be gained by shortening the existing lags (underfitting). As shown in the table, all these tests suggest that system (2) is an adequate representation of the data, as none of these modifications to system (2) is found acceptable. Further support to system (2) comes from the fact that the Breusch-Godfrey test evidenced no significant serial correlation in the residuals of the estimated equations.[2] Moreover, the Chow test could not reject the hypothesis of interperiod stability of the equations.[3] The coefficient estimates of system (2) are not reported here to conserve space, but are available from the authors upon request. Note, however, that it may be difficult to assign strict interpretations to these coefficients due to the reduced form nature of the equations (Sims (1980)).

[2]As Johnston (1984) argues, the virtue of the Breusch-Godfrey test is that it is a robust test against general autoregressive and moving-average processes. In view of the sample size, a third-order lag was assumed for the Breusch-Godfrey test.

[3]Following Farley, Hinich, and McGuire (1975), the midpoint for each equation was used as the breaking date in order to maximize the empirical power of the Chow test. For space considerations, the test results are not reported here, but are available from the authors upon request.

More important for the purpose in this paper, however, are the implied Granger-causality inferences.

Tests 18 through 25 reported in Table 2 provide the F-statistics to test the Granger-causal orderings in system (2)--i.e., imposing zero restrictions on the nonzero elements of system (2). The hypothesis that the degrees of operating and financial leverage do not Granger-cause beta cannot be rejected. Specifically, the FPE procedure proposed a zero element in model (2) for both variables in the beta equation. Thus, even a weak form of causality running from DOL and DFL to beta was not detected by the FPE criterion. In addition, when such restrictions were tested within the system of equations, they were not rejected. (See tests 1 and 2 in Table 2.) In contrast, the reverse hypothesis that beta does not Granger-cause DOL is strongly rejected, as evident in test 20 of Table 2. Therefore, there appears to be a unidirectional Granger-causality flowing from beta to DOL without significant feedbacks. Interestingly, the results also reject the hypothesis that beta Granger-causes DFL. (See test 4 in Table 2.) Thus, one can infer that beta and DFL are causally independent.

Based on these findings, any observed correlation between beta and the degree of financial leverage (at least for the company under study) is elusive and is simply the outcome of the two variables responding to other factors. Moreover, any observed correlation between beta and the degree of operating leverage (for the same company) primarily is due to the former causing the latter. This is contrary to what usually is hypothesized.

To provide further evidence on this issue, the common correlation-based analysis was followed--beta was regressed against the contemporaneous values of the three independent variables (the degrees of operating and financial leverage and the intrinsic business risk) over the same estimation period as before. The following equation was obtained using ordinary least squares:

$$\underset{}{\beta_t} = \underset{(4.97)}{-0.291} - \underset{(2.13)}{1.136}\, p_t - \underset{(1.14)}{0.639}\, f_t - \underset{(1.09)}{3.124}\, v_t$$

$R^2 = 0.21$, SEE = 0.297

where:

SEE = the standard error of the regression, and the numbers in parentheses below the coefficient estimates are the absolute values of the t-statistics.

Interestingly, these regression results suggest a strong effect of DOL on beta that is statistically significant at the 5 percent level.[4] The correct interpretation of such a finding for the company under study is not that DOL has caused changes in beta, however, but that beta has caused changes in DOL. This illustrates the usefulness of the proposed VAR technique over the potentially misleading correlation-based procedure for analyzing the relationship between beta and the accounting variables.

The VAR results are also useful in examining other causal linkages among the variables. For example, DOL does not exert even a weak Granger-causal impact upon DFL. On the other hand, some weak causality in the reverse direction from DFL to DOL was revealed. This reverse causality is not statistically significant, however, even at the 10 percent significance level. (See test 22 in Table 2.) Thus, the two variables could be considered causally independent. Moreover, only intrinsic business risk seems to have Granger-caused beta, though this causal impact is only of the weak form, as seen in test 19. At the 10 percent level, however, the reverse hypothesis that beta does not Granger-cause IBR is not rejected. (See test 24.) Thus, there appears to be some degree of bidirectional causality between beta and the intrinsic business risk suggesting the simultaneous determination of the two variables. Consequently, instead of the more common single equation approach, the results suggest that a more fruitful inquiry into the relationship between beta and the intrinsic business risk, at least for the company under study, should be performed in the context of a simultaneous equation model.

Concluding Remarks

Based on prior theoretical considerations, this paper formulates and estimates a four variable vector autoregressive (VAR) model for a randomly selected company over a 32 year period. The variables studied are beta, the degree of operating leverage, the degree of financial leverage, and the intrinsic business risk.

In examining the relationship between beta and these accounting variables, previous studies typically have employed some correlation-based analyses. This paper argues that such an approach is inadequate and cannot discriminate between four alternative hypotheses. These equally plausible hypotheses are that the accounting variables cause changes in beta (the implicit and commonly made assumption), that beta causes changes in the accounting variables, that beta and the accounting variables are causally independent, and that beta and the

[4]The simple correlation coefficient between beta and DOL is equally high at -0.35.

accounting variables are mutually causal. A significant correlation on the accounting variables in a beta equation, of the type reported for example by Mandelker and Rhee (1984), is consistent with any of these hypotheses.

To conduct proper tests of these alternative hypotheses, a multivariate VAR modeling technique was used in this paper. The estimated VAR model was subjected to extensive diagnostic checking, and the model proved to be an adequate representation of the data.

The results from the VAR-system modeling technique consistently reject the common hypothesis that the accounting variables have caused beta for the company selected. Instead, the results indicate that beta has caused significant changes in the degree of operating leverage. For beta and the degree of financial leverage, the VAR results reveal no significant causal ordering between the two variables for the company under study. Thus, beta and the degree of financial leverage are essentially causally independent, making any observed correlation between them elusive. A similar finding also is obtained to some extent for the relationship between DOL and DFL. Consequently, any cross correlation between these two variables (such as that found by Mandelker and Rhee) also could be elusive and primarily the result of both variables responding to other factors. Finally, some bidirectional causality is found between beta and the intrinsic business risk. Thus, the typical single equation approach of beta determination in which the IBR variable is treated as exogenous could yield erroneous results. A more fruitful inquiry into the relationship between beta and the intrinsic business risk should follow a simultaneous equation framework.

The results in this paper are generated from applying the VAR modeling technique to one randomly selected company. The results, therefore, may be sensitive to the testing technique used and/or unique with the particular company studied. Consequently, these results should be interpreted with caution. At the very least, though, these results do highlight the usefulness of the VAR technique for studying the causal relationship underlying the beta decomposition model.[5]

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[5] Although this paper's main interest lies in the nature of the causality linkage, a possible extension is to use the resulting VAR model for forecasting analysis, a task that is beyond the scope of this paper. On this, see Litterman (1979) and Hakkio and Morris (1984).

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Table 1
Variable Definitions

Name of the Variable	Definition and Computation
Beta (β_t)	The slope of the characteristic line between the returns on GSU stock and those on S&P 500 over a 60 monthly holding period ending in t. (For example, for the 1956 beta, monthly returns for the period 1952-1956 were used.)
Degree of Operating Leverage (DOL_t)	The slope of the regression line of the annual EBIT on the log of annual sales over a ten year period ending in t. (For example, for the 1956 DOL, the two variables for the period 1947-1956 were used.)
Degree of Financial Leverage (DFL_t)	The slope of the regression line of the log of annual earnings after taxes (EAT) on the log of EBIT using a ten year period ending in t. (For example, for the 1956 DFL, the two variables for 1947-1956 were used.)
Intrinsic Business Risk (IBR)	$[cor(\tilde{R}_{mt}, ROE_t) \times \sigma_{\tilde{R}mt} \times \sigma_{ROE_t}] / \sigma^2_{\tilde{R}mt}$ where $\tilde{R}_{mt}$ = the rate of return on the market portfolio for the period from t-1 to t, and $ROE_t = (Sales_t/Common\ Equity_{t-1}) \times (EAT_t/Sales_{t-1}.)$

Table 2

F-Statistics for Various Hypotheses Tests
Using System (1) as the Maintained Hypothesis

Hypothesis		F-Statistic
(1)	$a_{12}^{2}(L) = 0$	0.76
(2)	$a_{13}^{2}(L) = 0$	1.18
(3)	$a_{24}^{2}(L) = 0$	1.74
(4)	$a_{31}^{2}(L) = 0$	0.36
(5)	$a_{32}^{2}(L) = 0$	1.04
(6)	$a_{34}^{2}(L) = 0$	1.72
(7)	$a_{42}^{2}(L) = 0$	1.28
(8)	$a_{43}^{2}(L) = 0$	0.69
(9)	$a_{11}^{5}(L) = 0$	0.92
(10)	$a_{14}^{3}(L) = 0$	2.76
(11)	$a_{21}^{3}(L) = 0$	2.60
(12)	$a_{22}^{3}(L) = 0$	0.51
(13)	$a_{23}^{4}(L) = 0$	1.21
(14)	$a_{33}^{3}(L) = 0$	0.30
(15)	$a_{41}^{3}(L) = 0$	0.52

Table 2 (continued)
F-Statistics for Various Hypotheses Tests
Using System (1) as the Maintained Hypothesis

Hypothesis	F-Statistic
(16) $a_{44}^{3}(L) = 0$	2.62
(17) $a_{11}^{1}(L) = 0$	6.74**
(18) $a_{11}^{3}(L) = 0$	44.40**
(19) $a_{14}^{1}(L) = 0$	0.52
(20) $a_{21}^{1}(L) = 0$	4.72**
(21) $a_{22}^{1}(L) = 0$	1.00
(22) $a_{23}^{2}(L) = 0$	1.70
(23) $a_{33}^{1}(L) = 0$	1.33
(24) $a_{41}^{1}(L) = 0$	3.00*
(25) $a_{44}^{1}(L) = 0$	4.46**

Note: An * indicates rejection of the hypothesis at the 10 percent level of significance, while ** indicates rejection of the hypothesis at the 5 percent level of significance