UNIVERSITY OF ALBERTA

THE CHOICE OF RETURN-GENERATING MODELS IN EVENT STUDIES AND RATIONALITY OF VALUE LINE'S QUARTERLY EARNINGS FORECASTS

BY

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THE CHOICE OF RETURN GENERATING MODELS IN EVENT STUDIES AND RATIONALITY OF VALUE LINE'S QUARTERLY EARNINGS FORECASTS

ABSTRACT

The thesis comprises two papers of which the abstracts are presented as follow.

THE CHOICE OF RETURN-GENERATING MODEL AND CROSS-SECTIONAL DEPENDENCE IN EVENT STUDIES

This paper examines the choice of return generating models for event studies with contemporaneous event periods and industry clustering (CEPIC). The importance of specifying an appropriate return-generating model in event studies with CEPIC is demonstrated by showing that if the return-generating model is the two-factor model, inferences based on the market model are invalid. The evidence that the two-factor model is a better return-generating model is presented. Further, the contemporaneous dependencies in the two-factor model residuals are found significant for the majority of the sampled industries. Finally, using an error components model, it is shown that the industry factor can explain on average 6.7 percent and 11.5 percent of the variation in market model residuals for daily and weekly returns respectively.

ON THE RATIONALITY OF VALUE LINE'S QUARTERLY EARNINGS FORECASTS

This paper provides a comprehensive test of the Muthian rationality of Value Line's quarterly earnings forecasts. Consideration is given to econometric issues arising from the use of overlapping data. The results are as follows. The primary conclusion is that the rationality of Value Line's quarterly earnings forecasts can be rejected for a majority of the firms. Value Line's quarterly earnings forecasts are biased. Irrationality of Value Line's forecasts is indicated by the existence of significant autocorrelation in forecast errors, which suggests that Value Line does not make optimal use of information available. This is further supported by the evidence on Value Line's inefficient use of the information contained in the historical earnings realizations and past forecasts. These results indicate that, if the market is efficient, Value Line's earnings forecasts are not necessarily good proxies for the market's earnings expectations. More importantly, this study suggests ways in which better earnings expectations can be obtained.

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THE CHOICE OF RETURN-GENERATING MODELS AND CROSS-SECTIONAL DEPENDENCE IN EVENT STUDIES

Abstract. This paper examines the choice of return generating models for event studies with contemporaneous event periods and industry clustering (CEPIC). The importance of specifying an appropriate return-generating model in event studies with CEPIC is demonstrated by showing that if the return-generating model is the two-factor model, inferences based on the market model are invalid. The evidence that the two-factor model is a better return-generating model is also presented. Both the analytical results and empirical evidence support the finding in Chandra and Balachandran (1990) that inferences using the generalized least squares (GLS) on the market model are very sensitive to return-generating model misspecifications. The results in this paper indicate that the findings in earlier event studies with CEPIC based on the market model need to be interpreted with caution. Further, the contemporaneous dependencies in the two-factor model residuals are found significant for the majority of the sampled industries. That is, the industry index in the two-factor model cannot remove all the cross correlations in the market model residuals. Therefore, even with the two-factor model as the return-generating model, GLS may be a preferred method for estimation and inferences and the test statistic for inferences has to be robust to the presence of cross-sectional dependencies. Finally, using an error components model, it is shown that the industry factor can explain on average 6.7 percent and 11.5 percent of variations in market model residuals respectively for daily and weekly returns. This implies that the industry effects are too important to ignore in event studies with CEPIC.

INTRODUCTION

The specification of return-generating models is a critical element of research design in event studies. Beaver (1981), Morse (1984), and Jain (1986), among others have analytically addressed the issue. Although there have been some simulation results on the choice of alternative models (e.g., Brown and Warner, 1980, 1985; Dyckman, Philbrick and Stephan, 1984; Brown and Weinstein, 1985; and Chandra, Moriarity and Willinger, 1990), simulation studies have primarily focused on the market model, either ignoring the multi-factor models or evaluating multi-factor models in the context of random samples. These simulation studies demonstrated that for event studies with diversified (random) samples, the market model seems to perform well, confirming the prediction of Beaver (1981, pp.179). However, little research has been conducted to address the return-generating model specification issue for event studies with contemporaneous event periods and industry clustering. This paper examines the choice of return-generating models for event studies with CEPIC.

Typical examples of event studies with CEPIC include the literature on the economic consequences of accounting regulation and policy changes and the studies on the measurement of intra-industry information transfers. The economic consequences literature investigates the impact of accounting regulation and policy changes such as leasing, and oil and gas accounting (e.g., Ro, 1978, on leasing; Collins and Dent, 1979, and Lev, 1979, on oil and gas accounting policy changes). Studies on intra-industry information transfers measure the impact of an information release on the stock prices of other firms in the same industry. For example, Foster (1981), Clinch and Sinclair (1987), Lev and Penman (1990), and Han and Wild (1990) studied the intra-industry information transfers associated with accounting earnings releases, while Baginski (1987), Han, Wild and Ramesh (1989), Pownall and Waymire (1989) examined information transfers for the releases of management earnings forecasts.

In event studies with CEPIC, market model residuals often exhibit significant contemporaneous cross-sectional correlations. Empirical evidence has accumulated on the magnitude of contemporaneous correlations in market model residuals. For example, Collins and Dent (1984) and Bernard (1987) have shown that intra-industry cross-sectional correlations are significant in the market model residuals. The magnitude of such cross correlations gets larger with the increase in the size of the portfolio (Collins and Dent, 1984) and the return interval (Bernard, 1987). Several studies indicated that the cross-sectional dependencies in market model residuals can severely bias the estimates of standard errors of the regression coefficients and threaten the validity of inferences based on procedures that assume independent residuals (e.g., Collins and Dent, 1984; Binder, 1985a, 1985b; Sefcik and Thompson, 1986; and Bernard, 1987). This implies that, for event studies in which sample firms are clustered over both time periods and industries, the problem of contemporaneous correlation has to be dealt with for both estimation and inference.

In market-based accounting and finance research, three different approaches have been taken to address the problem of contemporaneous cross-sectional correlations in market model residuals: the use of the generalized least squares method on the market model, the use of two-factor return-generating models, and the "difference in returns" (DIR) methods. The GLS method on the market model includes the application of Zellner's seemingly unrelated regression (SUR) and Sefcik and Thompson's (1986) portfolio approach. Shipper and Thompson (1983), Hughes and Ricks (1984), Lipe (1986), and Bernard (1987) are examples of applications of GLS in market-based accounting research. The advantages and disadvantages of GLS techniques have been discussed in detail in Binder (1985b) and Bernard (1987)[1].

In the second approach, the two-factor return-generating models are used to reduce residual cross-sectional correlations by employing an industry return index as a second factor in the return-generating models. The two-factor return-generating model has been used in several studies such as Langetieg (1978), Collins, Rozeff, and Dhaliwal (1981) and Han, Wild and Ramesh (1989)[2]. It seems that the use of the two-factor return-generating model has been motivated by evidence provided by studies on industry commonalities in stock returns (e.g., King, 1966; Fertuck, 1975; and Livingston, 1977).

The first two approaches to deal with cross-sectional dependencies have different implications for the specification of the underlying return-generating models. The use of GLS on the market model implicitly assumes that the market model is correctly specified and therefore only more sophisticated estimation and inference methods such as SUR need to be used to accommodate the existence of cross-sectional dependencies. On the other hand, the use of two-factor models implies that the market model is misspecified due to an omitted variable (specifically the industry return index). This paper demonstrates the importance of specifying an appropriate return-generating model in event studies with CEPIC and presents evidence that the descriptive adequacy of the market model versus the two-factor model as the return-generating model in event studies with CEPIC has to be empirically established. Further, this paper argues that residual behavior in the chosen return-generating model has to be examined in order to facilitate the choice of estimation methods and inference procedures[3].

The third approach (DIR method) has been applied in several studies (e.g., see Gonedes, 1975; Harrison, 1977; Abdel-khalik and McKeown, 1978; Beaver et al., 1980; Ro, 1980; and Vigeland, 1981). Beaver (1981) compared the DIR method with the (market model) residual return approach and suggested that "the difference in returns approach appears to have been motivated by concern over correlation among the market model residuals" (pp.179). Thompson (1989) presented analytical and simulation results that discredit the use of the DIR method where there are no cross-sectional dependencies in the market model residuals. In this study, the appropriateness of DIR approach in event studies with CEPIC is assessed.

In this paper: (1) It is shown that if the return-generating model is the two-factor model, inferences based on the market model residuals are invalid. (2) Econometric tests are conducted to assess the adequacy of the market models and the two-factor model as return-generating models for event studies with CEPIC. The validity of DIR methods is also evaluated. (3) Specification tests are conducted to examine the cross-sectional dependencies in the two-factor model residuals as well as in the market model residuals in order to facilitate the choice of estimation methods and test statistics. As discussed in Collins and Dent (1984), Chandra and Rohrbach (1990) and others, some of the test statistics used in event studies are not robust to heteroskedasticity and cross-sectional dependencies. Consequently, the residual behavior of the chosen return-generating model has to be examined so that valid inferences can be made. (4) The significance of the industry factor in explaining variation in the market model residuals is assessed.

The paper extends the literature in several directions. First, this study is the first to analytically address the issue of the choice of return-generating model for event studies with CEPIC. That is, the alternative return-generating models are evaluated in an industry context. Drawing from a standard result in econometrics, this study shows that if the return-generating model is the two-factor model, inferences based on the market model residuals are invalid. Second, the paper presents evidence that the two-factor model is the better return-generating model for the majority of the sampled industries. This implies that the results in earlier event studies with CEPIC based on the market model residuals need to be interpreted with caution. Further, the contemporaneous dependencies in the two-factor model residuals are found to be significant for the majority of the sampled industries. That is, the industry effects cannot remove all the cross correlations in the market model residuals. This is contrary to the assumption made by Beaver (1981, pp.178) that the two-factor model residuals are independent. Therefore, even with the two-factor model as the return-generating model, SUR may be a preferred method for estimation and inference and the test statistic for inferences has to be robust to the presence of cross-sectional dependencies. Finally, using an error components model, it is shown that the industry factor can explain on average 6.7 percent and 11.5 percent of variations in market model residuals respectively for daily and weekly returns. This implies that the industry effects are too important to ignore in event studies with CEPIC.

The paper proceeds as follows. In section 1, it is shown that if the data are generated by the two-factor model, inferences based on the market model residuals will be invalid. Section 2 discusses the econometric tests to be used in this study. The data and sampling issues are explained in section 3. Results and analysis are presented in section 4 and the summary and conclusions appear in section 5.

1. CONSEQUENCES OF INFERENCE BASED ON THE MARKET MODEL WHEN THE RETURNS ARE GENERATED BY THE TWO-FACTOR MODEL

The state of the art method in event studies with CEPIC is the SUR method on the market model with event dummies. In this section, a standard result on the impact of omitted variables in econometrics (see Johnson, 1984; Greene, 1990) is presented to show that the consequence of omitting the industry variable can be rather severe.

1.1. Specification of alternative return-generating models

a. The market model

The market model may be presented as:

$$\underline{R_{it}} = \underline{\alpha_i} + \underline{\beta_i}\ \underline{R_{Mt}} + \underline{e_{it}} \tag{1}$$

where:

R_{it} and R_{Mt} are the returns to security i and a market portfolio in period t respectively;

α_i and β_i are the intercept and slope coefficients for the security i. Both α_i and β_i are assumed to be firm-specific and time-stationary;

i is the firm index and $i = 1,\ldots,J$ (where $J>1$);

t is the time period index and $t = 1,\ldots,T$.

e_{it} are the ordinary least squares (OLS) residuals conditional on the market returns R_{Mt}, and e_{it} are subject to the following restrictions: $E(e_{it})=0$ for all i and t.

In vector form, the market model equation (1) may be rewritten as follows:

$$R_i = \mathbf{X}_{Mi}\,\delta_i + e_i \qquad \text{(1a)}$$

Where:

R_i is the T×1 time series vector of returns to security i (i.e., $R_i' = (R_{i1},\ldots,R_{It})$);

$\mathbf{X}_{Mi} = (L\ R_M)$ is a T×2 data matrix for security i where L is a column of ones and R_M is the T×1 time series vector of returns to the market portfolio (that is, $R_M' = (R_{M1},\ldots,R_{MT})$);

$\delta_i = (\alpha_i\ \beta_i)'$ is a 2×1 vector of regression coefficients.

As noted by Beaver (1981, pp.167), the model specified in equation (1) does not require the residuals to be cross-sectionally independent. Beaver (1981) suggested that e_{it} and e_{jt} can be correlated for $i \neq j$ due to the omitted common factors.

At the industry level, the system of the market models for all firms in an industry can be written as:

$$R_1 = \mathbf{X}_{M1}\ \delta_1 + e_1$$

$$R_2 = \mathbf{X}_{M2}\ \delta_2 + e_2 \qquad (1b)$$

$$\cdots\cdots$$

$$R_J = \mathbf{X}_{MJ}\ \delta_J + e_J$$

where:

J is the number of firms in that industry;

Σ_M is the time-invariant[4] contemporaneous covariance matrix of the market model residual returns in (1b).

$E(e_{it}\ e_{js}) = 0$ for all $s \neq t$, that is, no serial correlation and no cross-serial correlation[5].

It is a well recognized result that when the regressors are the same for all the firms in the same industry, the SUR estimates of the regression coefficients are the same as those under OLS and accordingly the residuals are the same under both SUR and OLS (see Schmidt, 1976). Therefore, the same notation for the regression coefficients and residuals are used.

The system (1b) can be stacked together as:

$$\begin{bmatrix} R_1 \\ R_2 \\ \cdot \\ \cdot \\ R_J \end{bmatrix} = \begin{bmatrix} \mathbf{X}_{M1} & 0 & \cdots & 0 \\ 0 & \mathbf{X}_{M2} & \cdots & 0 \\ & & \vdots & \\ 0 & 0 & \cdots & \mathbf{X}_{MJ} \end{bmatrix} \begin{bmatrix} \delta_1 \\ \delta_2 \\ \cdot \\ \cdot \\ \delta_J \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \cdot \\ \cdot \\ e_J \end{bmatrix}$$

$$R = \mathbf{X}_M\ B_M + E \qquad (1c)$$

where:

$R' = (R_1', \ldots, R_J')$;

$B_M' = (\delta_1', \ldots, \delta_J')$;

$E' = (e_1', \ldots, e_J')$;

$$\mathbf{X}_M = \begin{bmatrix} \mathbf{X}_{M1} & 0 & \dots & 0 \\ 0 & \mathbf{X}_{M2} & \dots & 0 \\ & & \vdots & \\ 0 & 0 & \dots & \mathbf{X}_{MJ} \end{bmatrix}$$

The covariance matrix for E is $\Omega = \Sigma_M \otimes I_T$ where I_T is the identity matrix of order T×T and $\otimes$ is the Kronecker product sign.

b. The two-factor return-generating model

The two-factor return-generating model may be specified as:

$$R_{it} = a_i^I + b_i^M R_{Mt} + b_i^I R_{It} + u_{it} \qquad (2)$$

where:

R_{It} is the returns to the industry index in period t;

u_{it} is security i's residuals conditional on the realization of both R_{Mt} and R_{It};

a_i^I, b_i^M, b_i^I are assumed to be firm-specific and time-stationary parameters.

Following Beaver (1981, pp.178), the industry factor is assumed to have a zero mean ($E(R_{It})=0$) and to be orthogonal to the return to the market portfolio, that is, $Cov(R_{Mt},R_{It}) = 0$ (as this can be easily implemented in empirical work). Contrary to Beaver (1981), the contemporaneous cross-sectional correlations among the two-factor model residuals are not restricted to be zero.

The vector version of the two-factor model (2) may be written as:

$$R_i = X_{Ii}\,\gamma_i + u_i \qquad (2a)$$

Where:

$X_{Ii} = (L\ R_M\ R_I)$ is a T×3 data matrix for security i where L is a column of ones and R_M and R_I are the T×1 time series vector of returns to respectively the market portfolio (that is, $R_M' = (R_{\underline{M1}},\ldots,R_{\underline{MT}})$) and the industry index portfolio ($R_I' = (R_{\underline{I1}},\ldots,R_{\underline{IT}})$);

$\gamma_i = (a_{\underline{i}}^{I}\ b_{\underline{i}}^{M}\ b_{\underline{i}}^{I})'$ is a 3×1 vector of regression coefficients.

At the industry level, the system of the two-factor models for all firms in an industry may be written as:

$$
\begin{aligned}
R_1 &= \mathbf{X}_{I1}\ \gamma_1 + u_1 \\
R_2 &= \mathbf{X}_{I2}\ \gamma_2 + u_2 \qquad\qquad (2b) \\
&\ldots\ldots \\
R_J &= \mathbf{X}_{IJ}\ \gamma_J + u_J
\end{aligned}
$$

where:

Σ_I is the time-invariant contemporaneous covariance matrix of the two-factor model residual returns under SUR.

$E(u_{\underline{it}}\ u_{\underline{js}}) = 0$ for all $s \neq t$, that is, no serial correlation and no cross-serial correlation.

The stacked system may be written as:

$$
\begin{bmatrix} R_1 \\ R_2 \\ \cdot \\ \cdot \\ \cdot \\ R_J \end{bmatrix} = \begin{bmatrix} \mathbf{X}_{I1} & 0 & \ldots & 0 \\ 0 & \mathbf{X}_{I2} & \ldots & 0 \\ & & \cdot & \\ & & \cdot & \\ & & \cdot & \\ 0 & 0 & \ldots & \mathbf{X}_{IJ} \end{bmatrix} \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \cdot \\ \cdot \\ \cdot \\ \gamma_J \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ \cdot \\ \cdot \\ \cdot \\ u_J \end{bmatrix}
$$

$$
R = X_I\ B_I + U \qquad\qquad (2c)
$$

where:

$$
\mathbf{X}_I = \begin{bmatrix} \mathbf{X}_{I1} & 0 & \ldots & 0 \\ 0 & \mathbf{X}_{I2} & \ldots & 0 \\ & & \cdot & \\ & & \cdot & \\ 0 & 0 & \ldots & \mathbf{X}_{IJ} \end{bmatrix}
$$

$R' = (R_1', \ldots, R_J')$

$B_I' = (\gamma_1', \ldots, \gamma_J')$;

$U' = (u_1', \ldots, u_J')$;

The covariance matrix for U is $\Pi = \Sigma_I \otimes I_T$.

c. The dummy variable model

The third model to be investigated is a dummy variable model which may be presented as:

$$
\begin{aligned}
\underline{R_{1t}} &= \underline{c_1} + \underline{d_1}\ \underline{R_{M,t}} + \underline{\lambda_t} + \underline{w_{1t}} \\
\underline{R_{2t}} &= \underline{c_2} + \underline{d_2}\ \underline{R_{M,t}} + \underline{\lambda_t} + \underline{w_{2t}} \qquad (3) \\
&\ldots\ldots\ldots \\
\underline{R_{Jt}} &= \underline{c_J} + \underline{d_J}\ \underline{R_{J,t}} + \underline{\lambda_t} + \underline{w_{Jt}}
\end{aligned}
$$

where:

$\underline{\lambda_t}$ are treated as fixed parameters in (3).

$\underline{\lambda_t}$ are designed to capture the effect of industry-specific variables on the stock returns in period t. The motivation for proposing this dummy variable model is that this model is a statistical representation of the DIR methods used in accounting literature (e.g., Harrison, 1977; Baginski, 1987)[6].

This dummy variable model is a special case of the two-factor market model where industry beta $\underline{b_i^I}$s in equation (2) are assumed to be the same for all firms in the same industry. That is, $\underline{b_i^I} = \underline{b_j^I}$ for all i and j.

1.2. The consequences of misspecifying the return-generating models

The purpose of this section is to show that the consequences of misspecifying the return-generating models can be serious in that such misspecification invalidates the inference. Given the general result on the omitted variable problem in econometrics, it is shown that, even in the very favorable situations in which the omitted industry variable has zero unconditional mean and is orthogonal to the return to the market portfolio, inferences based on the market model will be invalid if the two-factor model is the true model[7].

Suppose that the returns are generated by the two-factor model (2a): $R_i = \mathbf{X}_{Ii}\ \gamma_i + u_i$ where $u_i \sim N(0,\underline{\sigma_u}^2 I_T)$, however, the market model (1a): $R_i = \mathbf{X}_{Mi}\ \delta_i + e_i$ where $e_i \sim N(0,\underline{\sigma}^2 I_T)$ is used for estimation and inference and the variable R_I is omitted. This is a standard omitted variable problem in econometrics, thus results can be borrowed directly from the econometrics textbooks by Johnston (1984) and Greene (1990). Riddle and Buse (1980) provided a more formal and unified treatment of the omitted variable problem in the framework of restricted least squares.

Suppose the analysis is conducted at the individual firm level and OLS is applied to the market model (1a), then the OLS estimator of the regression coefficients (of Firm i) $\delta_{iOLS} = (\mathbf{X}_{Mi}'\mathbf{X}_{Mi})^{-1}\ \mathbf{X}_{Mi}'R_i$. Here $\mathbf{X}_{Mi}$ may be interpreted as all the variables in the estimated model which could include event dummy variables. Accordingly, $\mathbf{X}_{Mi}$ is assumed to have an order of $\underline{k_i} \times T$. Next, two issues are addressed: the unbiasedness of δ_{iOLS} and the validity of the inference.

(1) The unbiasedness of δ_{iOLS}

Proof: $\delta_{iOLS} = (\mathbf{X}_{Mi}'\mathbf{X}_{Mi})^{-1}\mathbf{X}_{Mi}'R_i$

$= (\mathbf{X}_{Mi}'\mathbf{X}_{Mi})^{-1}\mathbf{X}_{Mi}'(\mathbf{X}_{Ii}\ \gamma_i + u_i)$ as the true model is (2a)

$$= (\mathbf{X}_{Mi}'\mathbf{X}_{Mi})^{-1}\mathbf{X}_{Mi}'(\mathbf{X}_{Mi}\ \delta_i + R_I\ b_i + u_i) \text{ as } \mathbf{X}_{Ii} = (\mathbf{X}_{Mi}\ R_I)$$

$$= \delta_i + (\mathbf{X}_{Mi}'\mathbf{X}_{Mi})^{-1}\mathbf{X}_{Mi}'R_I\ b_i + (\mathbf{X}_{Mi}'\mathbf{X}_{Mi})^{-1}\mathbf{X}_{Mi}'u_i$$

$$E(\delta_{iOLS}) = \delta_i + E[(\mathbf{X}_{Mi}'\mathbf{X}_{Mi})^{-1}\mathbf{X}_{Mi}'R_I b_i]$$

Therefore, $E(\delta_{iOLS}) \neq \delta_i$ unless either $\mathbf{X}_{Mi}'R_I = 0$. That is, the OLS estimator of the regression coefficients is biased unless the omitted variable R_I is orthogonal to the included variables $\mathbf{X}_{Mi}$.

(2) Inferences on δ_{iOLS}

In event studies, the primary interest is to assess statistical significance of the regression coefficients of the event dummy variables. The validity of inference based on the market model (while the two-factor model is the true model) is evaluated.

The estimate of the variance of δ_{iOLS} is $Var(\delta_{iOLS}) = \sigma^2(\mathbf{X}_{Mi}'\mathbf{X}_{Mi})^{-1}$. For inferences, an estimate of $\underline{\sigma}^2$ is required. The OLS estimator of $\underline{\sigma}^2$ is $s^2 = e_i'e_i\ /(T-k_1)$ where k_1 is the number of the variables included in the estimated model. Riddle and Buse (1980), Johnston (1984, pp.259-261) and Greene (1990, pp.261) proved that s^2 is biased upward.

Proof:

Let $\mathbf{M}_1 = I - \mathbf{X}_{Mi}(\mathbf{X}_{Mi}'\mathbf{X}_{Mi})^{-1}\mathbf{X}_{Mi}'$

$$E(e_i'e_i) = b_i'R_I'\mathbf{M}_1R_Ib_i + \underline{\sigma_u}^2\ \text{Trace}(\mathbf{M}_1)$$

$$= b_i'R_I'\mathbf{M}_1R_Ib_i + \underline{\sigma_u}^2\ (T-k_1)$$

$$E(s^2) = (b_i'R_I'\mathbf{M}_1R_Ib_i)/(T-k_1) + \sigma_u^2$$

As the quadratic term in the above equation is positive semidefinite (see Johnston, 1984, pp.261), s^2 is biased upward. This upward bias in s^2 in turn implies that the null hypothesis would be accepted too often (Riddle and Buse, 1980, pp.213) and faulty inferences would be made.

To summarize, when the true return-generating model is the two-factor model, inferences based on the market model will be invalid. In general, both the OLS estimator of the regression coefficients and the estimator of their variances are biased and thus correct inferences are not available unless the correct model (the two-factor model) is used. If the omitted variable is further restricted to be orthogonal to the included variables in the estimated model, the estimator of the coefficients is now unbiased; however, the estimator (s^2) of the disturbance variance is still biased upward. The results from the proceeding omitted variable analysis have implication for event studies with CEPIC where the market model is used while the two-factor model is the correct return-generating model. First, to the extent that the event dummy variables are correlated with the omitted industry return index, the use of the market model produces a biased estimator of the regression coefficients for the event dummy variables and faulty inferences about the significance of the events. Second, even if the event dummy variables are orthogonal to the industry index, the use of the market model would <u>underestimate</u> the significance of the events as the estimator of the disturbance variance is biased upward. This provides analytical support for the finding in Chandra and Balachandran (1990) that GLS on the market model can produce invalid inferences if the return generating model is misspecified.

To summarize, it is the concern over faulty inferences based on the market model (when the two-factor model should be used), not the ability of the industry index to reduce the cross-sectional correlations in market model residuals, that provides a compelling support for the use of the two-factor model.

2. SPECIFICATION TESTS

2.1. A model choice test

It is important to stress that the existence of significant contemporaneous correlation in market model residuals does not necessarily imply the superiority of the two-factor return model over the market model. For example, if the covariation in the market model residuals is due to the omitted industry factors that cannot be measured and have to be left in the disturbance, the market model would be correctly specified. Therefore, the validity of using a two-factor model as a return-generating model has to be established empirically.

As the market model and the dummy variable model are special cases of the more general two-factor model, the following tests are conducted on the two-factor model for each of the sampled industries.

First, the hypothesis (zero industry betas) H_1: $b_i^I = 0$ for all i (i.e. all firms in an industry) is tested. If the hypothesis H_1 is accepted, then the market model would be an appropriate return-generating model for that particular industry. On the other hand, rejection of hypothesis H_1 would suggest that the market model is misspecified due to the omitted industry variable and the two-factor market model is a better return-generating model.

The tests of H_1 are conducted on an industry basis. That is, the return-generating models of all firms in an industry are considered as disturbance-related sets of regression equations. Accordingly, hypothesis H_1 can be specified as a set of linear restrictions on the coefficient vector of the seemingly unrelated regressions. Two test procedures used to test H_1 are the Wald test and the extended F-type test in the SUR context.

The Wald tests are based on the maximum likelihood estimators of regression coefficients and covariance matrix Ω. The Wald statistic for testing H_1 is

$$\underline{\pi_W} = \{\hat{e}'(\hat{W}_I \otimes I_T)\ \hat{e}\} - \{\hat{u}'(\hat{W}_I \otimes I_T)\hat{u}\}$$

where $\hat{e}_{(JT\times 1)}$ are the market model residuals estimated by SUR, $\hat{u}_{(JT\times 1)}$ are the two-factor model residuals estimated by SUR. $\hat{W}_{I\ (J\times J)}$ is the covariance matrix estimator of Σ_I based on the two-factor model residuals, and I_T is an identity matrix of order T×T. The Wald statistic under H_1 has an asymptotic $X^2_{(J)}$ distribution where J is the number of firms in the industry.

The second test procedure is an extended version of the single-equation F-test. The extended F-test tends to reject H_1 less frequently than the Wald tests $\underline{\pi_W}$ (see Judge <u>et al</u>., 1985, pp.476). In general, this extended F-statistic is believed to have better finite sample properties than the Wald tests[8].

If the hypothesis H_1: $b_i^I = 0$ for all i is rejected, then we can assess the appropriateness of the dummy variable model by testing the uniform beta hypothesis H_2: $b_i^I = b_j^I$ for all i and j (where i≠j, and i, j = 1,2,...,J) in the same industry. The acceptance of this uniform beta hypothesis suggests that the dummy variable model may be used as a simplification of the two-factor model. As hypothesis H_2 imposes a set of linear restrictions on the coefficient vector of the two-factor model, the same test procedures (i.e., both the Wald test and the extended F-type tests) are applied to test for H_2.

A distinctive feature of this paper's approach to model evaluation lies in the fact that the model specification issues are evaluated in the context of SUR as opposed to the single-equation approach (OLS method) which has been used previously (e.g., Fertuck, 1975, pp.845)). To the extent that the two-factor model residuals are contemporaneously correlated, SUR approach is preferred to the OLS method for testing joint hypothesis such as H_1 and H_2 (as argued by Binder, 1985a; and others).

2.2. Test for the presence of contemporaneous .orrelation

Previous studies have focused exclusively on the cross-sectional correlation in market model residuals (e.g., see Livingston, 1977; Bernard, 1987). This paper examines cross-sectional dependencies in the two-factor model residuals as well as in the market model residuals.

The residuals of return-generating models are examined in order to determine appropriate estimation methods and choose appropriate test statistics for the specified hypotheses. Breusch and Pagan's (BP) (1980) Lagrange Multiplier (LM) procedures are applied to the return-generating models to test the hypothesis (H_0) of a diagonal covariance matrix for market model residuals and the hypothesis (H_3) of no cross-sectional dependencies in the two-factor model residuals (while a likelihood ratio (LR) test is used to test the hypothesis (H_0) in Livingston (1977) and Bernard (1987)). Although under the usual maximum likelihood regularity conditions the BP LM test is asymptotically equivalent to the LR test, the LM test is preferred due to its computational simplicity (as the LM test involves estimation with the restricted model and accordingly is often easier to implement than the corresponding LR or Wald tests).

It is important to emphasize that both BP LM and the LR tests for the existence of contemporaneous cross-sectional dependencies presume that the return-generating model is well specified. For industries where the industry effects are significant, the LR tests conducted by Livingston (1977) and Bernard (1987) on hypothesis H_0 based on the market model residuals may not provide valid inferences.

3. SAMPLING ISSUES AND INDUSTRY INDEX CONSTRUCTION

3.1. Sample issues and construction of industry indexes

The sample period for this study is from January 4, 1982 to December 31, 1986 for daily returns and from January 6, 1982 to December 31, 1986 for weekly returns. Weekly returns are constructed from the daily returns where a week is defined as from Wednesday to Tuesday. The four-year (1982 to 1986) period is chosen as the sample period to avoid the stock market crash in 1987 and to make nonstationarity a lesser concern.

Four-digit SIC code industry classifications on the Compustat File (Appendix B, 1989) are used as industry definitions. A total of 45 industries are identified with at least two firms in the Compustat Primary Industrial File (Appendix C, 1989, pp.5-7) which are listed primarily on NYSE. Firms in the 45 industries are also excluded from the sample if there are missing observations on the CRSP Daily Return File for the sample period. The use of firms in the Primary Industrial File is primarily motivated by the concern over the availability of daily return data and infrequent trading problems in the daily return data of small firms.

Table 1 about here

The final sample consists of 45 industries with a total of 229 firms, ranging from two to 20 firms per industry. **Table 1** presents the industry names and SIC codes in the final sample. The sample is comprehensive in that it consists of industries in different sectors such as manufacturing, service, retailing, transportation and entertainment. To further evaluate the representativeness of the sample, the following statistics are also reported in Table 1. There are approximately 2400 firms available in the Compustat Industrial Files, the number of firms in the 45 industries is 558 (including firms of the 45 industries in the Primary Industrial File, the Supplementary Industrial File, and the Tertiary File), which is 23.25 percent of the population. The Primary Industrial File consists of a total of approximately 800 firms, the number of firms in the sampled 45 industries is 329, which accounts for 41.125 percent of the firms in the Primary Industrial File. By requiring no missing observations in the sample period, the sample (329 firms) is further reduced by 100 to the final sample of 229 firms.

Table 2 about here

The classification of sampled industries according to the number of firms in the industry is provided in **Table 2**. The average number of firms per industry is slightly greater than five. However, the distribution is a very skewed one as 2-firm, 3-firm, 4-firm and 5-firm industries account for 75.6 percent of the sampled industries.

The final sample has both survivorship bias and size bias. Further, not all industries satisfying the sample criteria could be searched for because of cost constraints. The results obtained have to be interpreted in light of these possible limitations.

3.2. Industry index construction

Application of the two-factor models requires a construction of an industry return index. Two methods have been used in the literature to obtain the industry return index for firm i: the return on an equally-weighted (e.g., Fertuck, 1975) or a value-weighted (e.g., Han et al., 1989) industry portfolio excluding firm i, and an industry index that is constructed from factor analysis or principal components analysis (e.g., King, 1966; Livingston, 1977). Only an equally-weighted index is used here because prior studies suggest that the use of a value-weighted index will not alter the empirical results (e.g., see Han et al., 1989). Under either the equally-weighted or the value-weighted method, the derived industry index will differ across firms in the same industry; therefore, exact tests are not available in SUR (see Schipper and Thompson, 1985). The principal components approach is also attempted in order to assess the sensitivity of the results to the choice of the industry return index.

4. RESULTS AND ANALYSIS

The analyses are conducted on both daily returns and weekly returns to assess the sensitivity of the results to the choice of return intervals. This is important because of several problems with the daily returns, such as deviation from normality (e.g., Fama, 1976; Diacogiannis, 1986), nonsynchronous trading (e.g., Scholes and Williams, 1977) and infrequent trading problems (e.g., Dimson, 1979). (A five percent significance level is used throughout the analysis)

4.1. The market model

Breusch and Pagan's (1980) LM tests are applied to the daily and weekly returns of each sampled industry. That is, for a particular industry the BP procedure is conducted to test for a diagonal covariance matrix (H_0) for the disturbance-related market model regression equations of all firms in that
particular industry.

Table 3 and 4 about here

The detailed industry by industry results of testing H_0 on market model residuals are reported in **Table 3**. **Table 4** shows the summary statistics of results in Table 3. For daily returns (Panel A, Table 4), the hypothesis H_0 of no contemporaneous correlation is rejected for 39 out of the 45 industries while for weekly returns (Panel B, Table 4), the hypothesis H_0 is rejected for 37 out of the 45 industries. This is consistent with the finding in Bernard (1987) that contemporaneous dependencies are significant for most of the industries. Table 4 also indicates that cross-sectional correlation is not present in all industries (that is, H_0 is not rejected for every industry). This is consistent with the finding in Livingston (1977, pp.861). An implication of this finding is that, even if the market model is an appropriate return-generating model, for efficient estimation and correct inference the residuals behavior has to be examined on an industry by industry basis.

However, the fraction of industries for which H_0 is rejected is much higher than reported by Bernard (1987). Specifically, the rejection rates for H_0 are 86.9 percent for daily returns (see Panel A, Table 4) and 82.2 percent for weekly returns (see Panel B, Table 4) while the rejection rates in Bernard's (1987, pp.9) are 51 percent for daily returns and 78 percent for weekly returns. This difference may be due to the use of different industry definitions (Bernard, 1987, used three-digit SIC industry definitions).

The finding that the contemporaneous correlation is more significant for daily returns than for weekly returns is contrary to the result obtained by Bernard (1987).

4.2. The two-factor return-generating models

Table 5 and Table 6 present the specification test results for the two factor model where the industry index is constructed by the simple average return method.

Table 5 and 6 about here

Table 5 provides the results of testing Hypothesis H_1 (zero industry betas) and Hypothesis H2 (uniform industry betas) on an industry by industry basis. Summarized results are shown in Table 6. The results on testing H_1 are summarized in Panel A, Table 6. The hypothesis H_1 is rejected for 43 out of the 45 (95.6 percent) industries for daily returns and 42 out of the 45 (93.3 percent) industries for weekly returns. This suggests that the market model is misspecified and the two-factor model is a better return-generating model for most of the industries in the sample. Further, by comparing the result of testing H_0 on the market model with the result of testing H_1 on the two-factor return-generating model, it becomes apparent that insignificant cross-sectional correlations in market model residuals do not necessarily imply the insignificance of the industry betas. The rejection of H_1 for the majority of the sampled industries also raises questions as to the appropriateness of testing the hypothesis of no cross-section correlation based on the market model residuals (as in Bernard, 1987).

Panel B of Table 6 summarizes the results of testing H_2. For daily returns, hypothesis H_2 (uniform industry betas) is rejected for 26 out of the 45 (57.8 percent) industries. For weekly returns, H_2 is rejected for 22 out of the 45 (48.9 percent) industries. This suggests that the matching (DIR) method may be used to catch the firm-specific effects for the industries only when H_2 is accepted. However, the DIR approach is likely to underestimate the effects of events that have both industry-wide and firm-specific impacts, as some treatment effects (i.e., the industry effect) are matched out.

The cross-sectional correlations in the two-factor model residuals are examined by testing H_3 using the BP LM test. This paper is the first to examine the cross-sectional correlation in the two-factor model residuals. The detailed results can be found in Table 3 (the column under H3) while the findings are summarized in Panel C, Table 6. Previous studies, such as Fertuck (1975, pp.845) and Han et al. (1989), have assumed zero cross-sectional dependence in the two-factor model residuals. The results in Panel C of Table 6 suggest that this is no longer appropriate. For daily returns H_3 is rejected for 35 out of the 45 (77.8 percent) industries and for weekly returns H_3 is rejected for 29 out of the 45 (64.4 percent) industries. This has direct implications for return-generating model evaluations and for estimation and inference in event studies with CEPIC. For model evaluations, this implies that, for industries in which H_3 is rejected, specification tests on the two-factor model are better conducted with SUR (whenever feasible) rather than with OLS. For event studies with CEPIC, SUR may provide more efficient estimation than OLS (as used in Han et al., 1989). The existence of cross-sectional correlations in the two-factor model residuals also suggests that care is needed in the choice of test procedures for abnormal returns in event studies. For industries with significant cross-sectional dependencies in the two-factor model residuals, test statistics that do not require the assumption of independent residual returns are warranted. Examples of the test procedures are the t-test based on the mean residual returns and the nonparametric rank test proposed by Corrado (1989).

Finally, the same evidence as found in the context of the market model is documented for the two-factor model (see Panel c, Table 6): the contemporaneous correlation is more significant for daily returns than for weekly returns.

Several observations can be made by comparing the results of testing H_0, H_1, H_2, and H_3. The first observation is on the effectiveness of the industry return index in reducing intra-industry cross correlations in the market model residuals. **Table** 3 presents the industry by industry results of testing H_0 and H_3 in a comparative format, which facilitates an evaluation of the effectiveness of the industry index in reducing the cross-sectional dependencies in the market model residuals. The results in Table 3 indicate that the industry index is not very effective in eliminating <u>all</u> the intra-industry covariation in the market model residuals. Specifically, for daily returns (Panel A, Table 3), the industry return index captures all the intra-industry covariation in the market model residuals for only 4 (=39-35) out of the 39 industries (where the H_0 is rejected) while for weekly returns (Panel B, Table 3), the use of the industry factor completely eliminates all the intra-industry cross correlations in the market model residuals for only 8 (=37-29) out of the 37 industries (where the H_0 is rejected). As argued in the proceeding section of the paper, the importance of the two-factor model should not be judged only on the effectiveness of the industry index in reducing the cross-sectional correlations in the market model residuals, should instead be based on the results of testing H_1.

A second observation is on whether the results of testing H_0 can be used to justify the use of the two-factor model as the return-generating model. The answer to this question can be provided by comparing the summarized testing results on H_0 (Table 4) and H_1 (Table 6). For daily returns, H_0 is rejected for 39 industries (Panel A, Table 4) while H_1 is rejected for 43 (Panel A, Table 6). For weekly returns, H_0 is rejected for 37 industries (Panel B, Table 4) while H_1 is rejected for 42 industries (Panel B, Table 6). It follows that the absence of the significant cross-sectional correlations do not necessarily suggest adequacy of the market model.

Alternative methods of constructing the industry index are also evaluated. Livingston (1977, pp.861) has criticized the principal components and factor analysis approach to derive the industry-return index on the ground that the factor analysis approach is sample sensitive and (factor analysis) method sensitive and may fail to extract the industry effects. The results in this study are consistent with these criticisms. The BP LM test results suggest that the simple average method of constructing the industry-return index is better than the principal components method in that the simple average residual return method of constructing the industry index is more effective in reducing the cross-sectional correlation in the two-factor model residuals than is the principal components approach. This conclusion holds for both daily and weekly returns. For example, when daily returns are used, the principal components procedures applied to the market model residuals fail for 8 out of 45 industries. For the 37 industries in which the principal components procedure is not failed, the hypothesis of no cross-sectional correlation is rejected for all of the 37 industries. This suggests that even if the principal components analysis is applicable, the derived industry factor cannot remove the cross-sectional dependence as effectively as can the one derived from the simple average residual return method. To summarize, the results favor the use of the average residual return method in deriving the industry effect index while they do not support the principal components approach.

4.3. The significance of the industry-specific returns: an error components model approach

4.3.1. The error components model

Given that the industry betas are statistically significant for the majority of the sampled industries, the importance of these industry-specific commonalities in explaining variations in returns is assessed. Specifically, the following question is asked: how much of the variations in the market model residuals can be explained by the industry return index? This question is addressed in the context of an error components model which can be presented as:

$$\begin{aligned}
R_{1t} &= c_1 + d_1 R_{M,t} + \mu_t + \pi_1 + v_{1t} \\
R_{2t} &= c_2 + d_2 R_{M,t} + \mu_t + \pi_2 + v_{2t} \qquad (4) \\
&\cdots\cdots\cdots \qquad \cdots\cdots\cdots\cdots \\
R_{Jt} &= c_J + d_J R_{M,t} + \mu_t + \pi_J + v_{Jt}
\end{aligned}$$

where:

$\underline{\mu_t} \sim N(\underline{\delta}^2{}_{\mu}\ )$, $\underline{\pi_i} \sim N(0,\ \underline{\delta^2\pi})$ and $v_{\underline{it}} \sim N(0,\ \underline{\delta^2_v})$.

The error components model assumes that the error term of the regression consists of three independent components: the time-effects (or industry effects) $\underline{\mu_t}$, which change with time; the firm-specific effects $\underline{\pi_i}$, which are associated with the cross-sectional unit i; and the third component $v_{\underline{it}}$, which vary across both time periods and cross-sectional units. Furthermore, the components $\underline{\mu_t}$, $\underline{\pi_i}$, and $v_{\underline{i,t}}$ are subject to the following restrictions:

$E(\underline{\pi_i}\ v_{\underline{it}}) = E(\underline{\pi_i}\ \underline{\mu_t}) = E(\underline{\mu_t}\ v_{\underline{it}}) = 0$

$E(\underline{\pi_i}\ \underline{\pi_j}) = 0$ for all $i \neq j$, $E(\underline{\mu_s}\ \underline{\mu_t}) = 0$ for all $s \neq t$,

$E(v_{\underline{it}}\ v_{\underline{jt}}) = E(v_{\underline{is}}\ v_{\underline{it}}) = E(v_{\underline{it}}\ v_{\underline{js}}) = 0$ for all $i \neq j$ and $s \neq t$.

Taking all the assumptions together, the error components model imposes several restrictions on the covariance structure of the error terms (Judge et al., 1985, pp.530-537; Kmenta, 1986, pp.625-630) for further discussions on the error components model). First, define $f_{\underline{it}} = \underline{\pi_i} + \underline{\mu_t} + v_{\underline{it}}$. Then the above assumptions restrict $f_{\underline{it}}$ to be homoskedastic with the total variance given by Var $(f_{\underline{it}}) = \underline{\delta_\pi}^2 + \underline{\delta_\mu}^2 + \underline{\delta_v}^2$. Further, the error components model specifies homogeneous correlation between $f_{\underline{it}}$ and $f_{\underline{jt}}$ for $i \neq j$. Note that in the error components model the data constructs the industry index by itself, that is, $\underline{\mu_t}s$ are estimated directly from the model rather than constructed by the arbitrary methods used in the above. Within the framework of the error components model, the portion of Var$(f_{\underline{it}})$ explained by the time-effects $\underline{\phi_t}$ is given by $\varsigma_\phi = \underline{\sigma_u}^2 + (\underline{\sigma_u}^2 + \underline{\sigma_\pi}^2 + \underline{\sigma_v}^2)$ while the portion of Var$(f_{\underline{it}})$ accounted for by the firm-specific effects $\underline{\pi_i}$ is given by $\varsigma_{\underline{\pi}} = \underline{\sigma_\pi}^2 + (\underline{\sigma_u}^2 + \underline{\sigma_\pi}^2 + \underline{\sigma_v}^2)$. The difference between the error components model (4) and the dummy variable model is that the effects are treated as fixed parameters in (3) and as random variables in (4).

The use of the error components model to evaluate the importance of the industry index in explaining the variations in individual returns can be justified for the following reasons. First, the coefficients of multiple determination for the SUR system are difficult to interpret (see Judge et al., 1985, pp.477; Greene, 1990, pp.513) for further discussions). Therefore, the importance of the industry index in explaining the variation in returns cannot be assessed directly from the coefficients of multiple determination for the SUR system. Second, the error components model may be considered as a parsimonious characterization of residual covariance, which is desirable for some event studies according to Bernard (1987, pp.41). Third, there have been some applications of this type of model recently in accounting research (e.g., see the use of the dummy variable version of the model in O'Brien, 1988, 1990, and Beaver et al., 1989).

4.3.2. Estimation, results and analysis

The error components model is estimated by using a two-step procedure. First, the market model is estimated and in the second step the market model residuals are analyzed using the error components structure specified by the error components model. This study uses a method proposed by Fuller and Battese (1974) for the estimation of the three variance components (i.e., σ_u^2, σ_π^2, σ_v^2). The results are reported as follows.

Table 7 about here

The results of the error components model analyses of market model residuals appear in **Table** 7. For daily returns (see Panel A), the time effects $\underline{\phi_t}$ explain on average 6.7 percent of the variations in the market model residuals (Var($\underline{f_{it}}$)). $\varsigma_{\underline{\phi}}$, ranging from zero percent to 16.7 percent, is distributed with a mean of 6.7 percent and a standard deviation of 4.36 percent. $\varsigma_{\underline{\pi}}$, the proportion of Var($\underline{f_{it}}$) accounted for by the firm-specific effects, is zero percent for every industry in the sample. This implies that any $\underline{\pi_i}$ cannot be consistently positive or negative and the firm-specific effects cannot be predicted ex ante (see Judge et al., 1985, pp.535)).

For weekly returns (see Panel B), $\varsigma_{\underline{\phi}}$ is distributed with a mean of 11.5 percent and a standard deviation of 7.173 percent ranging from zero percent to 31.6 percent. Again, $\varsigma_{\underline{\pi}}$ is 0 percent for all the industries in the sample.

Two conclusions can be drawn. First, the findings in section 4.2 that (1) the industry effects are significant for the majority of the sampled industries and (2) not all the industries have significant industry effects are confirmed. Second, the industry effects can explain a large proportion of the variations in the returns and this explained proportion increases when the return interval gets longer. Assuming that the market factor explains about 25 percent of the variations in returns, the industry effects can explain about 5.03 percent and 8.63

percent of the variation in daily and weekly returns respectively[9]. This implies that the industry factors (time-effects) are too significant to be ignored in event studies because accounting earnings can only explain "two to five percent for very narrow windows (two to five days) and four to seven percent for medium (a quarter) to very long (two to five years) windows" (see Lev, 1989, pp.159-164) for a summary).

5. SUMMARY AND CONCLUSION

The primary contribution of this paper is the demonstration of the importance of specifying an appropriate return-generating model in event studies with CEPIC. It is shown that, if the two-factor model is the correct return-generating model, the omitted industry variable can bias the estimates of both the regression coefficients and the disturbance variance, accordingly invalidating the inference based on the market model. Empirically, based on the sample of 45 industries, this study indicates that the two-factor model is a better return-generating model f· the majority of the sampled industries but not for all the sampled industries. This has several implications. First, the choice of return-generating model has to be made on the industry by industry basis. Second, the results obtained in prior CEPIC types of event studies (e.g., Schipper and Thompson, 1983, and Hughes and Ricks, 1984) that are based on the market model for inferences, have to be interpreted with caution, especially when they failed to reject the null hypothesis. Third, the significance of the industry variable also raises some questions as to the appropriateness of applying the LR statistic to test the hypothesis of a diagonal covariance matrix as in Livingston (1977) and Bernard (1987).

A final implication of rejecting H_1 is that the security market agrees with the SIC four-digit definition most of the time if the significance of the industry factor can be interpreted as the market's acceptance of the four-digit SIC industry definitions. The acceptance of H_1 (i.e., the industry factor is not significant) for some four-digit SIC industries could suggest two possibilities: either the derived industry index is not appropriate or the market defines industries differently from the four-digit SIC codes. The first possibility would indicate that more research on the optimal construction of the industry index is warranted. This study indicates that the simple average method of constructing an industry return index is preferred to the principal components analysis method. The second possibility would imply that the four-digit SIC industry definition may be refined according to the market's perception of industries as reflected in security-returns covariation.

Another contribution of this paper is the result that the absence of cross-sectional dependencies in the market model residuals does not necessarily imply the insignificance of the industry variable. That is, one cannot rely on testing the cross correlation in the market model residuals to assess the need for the two-factor return-generating models.

This paper also shows that the industry return indexes (or the time-effects) play an important role in explaining variations in the market model residuals. For event studies CEPIC, the industry factor in the return-generating models has to be controlled to allow for correct and reliable inferences. The cross correlations in residual returns of the two-factor models are significant for the majority of industries. This suggests that a multivariate approach such as SUR needs to be applied whenever feasible for estimation and inferences, even if the two-factor model is used as the return-generating model.

One phenomenon for which the paper does not provide a good explanation is that according to the BP LM test, the cross-sectional correlation is more significant for daily returns than for weekly returns. As is documented in this study, this conclusion holds for both the market model residuals and the two-factor model residuals. This result contrasts with evidence reported in Bernard (1987, Table 1, pp.9) which shows that the fraction of industries for which one rejects the hypothesis of no intra-industry cross-sectional correlation becomes larger when the return interval increases from daily to weekly.

An issue not examined in this paper is the exogeneity (at least weak exogeneity) of the constructed industry return index. The way the industry return indexes are constructed might make the exogeneity of the industry indexes a valid concern. This is a very important issue because the correlation between the constructed industry return index and the disturbances may invalidate all the inferences based on the model with not so exogenous industry indexes. Hausman's (1978) specification tests provide a ready framework to test for the exogeneity of the industry return indexes. Neither has this paper studied the issue of causality. Both issues will be left for future research.

Further research could also explore the issue of optimal construction of the industry index. The use of security return data to refine the SIC industry definitions is another area for further study. The results also suggest the need to replicate the earlier CEPIC types of event studies with a careful choice of the return-generating models.

FOOTNOTES:

1. Among others, Schipper and Thompson (1983), Binder (1985) advocated the superiority of SUR in dealing with cross-sectional correlation. However, Chandra and Balachandran's (1990) simulation results discredit the use of SUR and support the application of Sefcik and Thompson's (1986) portfolio approach.

For SUR to be applicable, the following condition (Press (1972)) has to be satisfied: $(T-1)/2 \geq N$ where T is the number of time series observations and N is the number of cross-sectional units. For panel data where this inequality condition is not satisfied (and therefore, GLS method cannot be applied), Froot (1989) proposed a method-of-moments estimator which can account for both contemporaneous correlation and heteroskedasticity. Affleck-Graves and McDonald (1990) offered some alternatives for applications with relatively large N and small T.

2. Brown and Weinstein (1985), and Chen, Copeland and Mayers (1987), among others, have explored the usefulness of multi-factor return-generating models in event studies.

3. For detailed discussions on the choice of test statistics in various event studies, see Jaffe (1974), Collins and Dent (1984), Brown and Warner (1985), Corrado (1989), Chandra and Balachandran (1990) and Chandra and Rohrbach (1990).

4. The finance literature (e.g., Lo and MacKinlay, 1988) has shown that individual security returns are negatively autocorrelated while the market indexes exhibit positive autocorrelation. Lo and MacKinlay (1990) provided evidence on the positive cross-autocorrelation of stock returns. This paper presumes zero autocorrelation and zero cross-autocorrelation.

Several recent studies in the finance and economics literature (e.g., Lamoureux and Lastrapes, 1990; Schwart and Seguin, 1990; Pagan and Schwert, 1990) have shown that there are some ARCH, GARCH and EGARCH effects in stock returns. That is, stock returns tend to exhibit conditional heteroskedasticity. This suggests that the denominator in Beaver's (1968) U statistic should be the conditional variance of the return rather than the unconditional variance.

5. Pagan and Schwert (1989) constructed several nonparametric tests for covariance stationarity and provided evidence on the nonstationarity of covariance based on monthly returns over long time periods (1934 to 1987). The daily returns and weekly returns used in this study cover a four-year period; therefore, the nonstationarity of the covariance matrix may not be a major concern. In this study, a time-invariant covariance matrix is assumed.

6. The matching method (also called the difference-in-return model by others such as Thompson (1989)) has been commonly used as an alternative control mechanism in event studies (e.g., Gonedes, 1975; Harrison. 1977; Ro, 1980; Beaver, Christie and Griffin, 1980; and Vigeland, 1981). Basically, the residual is taken as the differences between the stock

return of a control firm and that of a treatment firm, that is $e_{it} = R_{it}-R_{jt}$ where R_{it} and R_{jt} are respectively the stock return for treatment firm i in period t and the stock return for control firm j in period t.

The primary advantage is its potential control for other confounding factors such as size and industry as well as systematic returns. One problem with the matching method is the difficulty in identifying all the relevant dimensions that need to be matched. Another problem (among others) with the matching method is its underlying assumption that the returns of both treatment firm i and control firm j share the same industry beta and the betas for the factors being controlled in the study. This assumption of homogeneous betas (or regression coefficients) may not be reasonable in many circumstances.

7. A similar issue has been discussed in Morse (1984, pp.616) and Jain (1986) where they examined the consequences of omitting some variables that are priced in equilibrium.

There are important differences between asset-pricing models and return-generating models (see Jain, 1986, for some other comments). Asset-pricing models such as CAPM and APT are concerned with cross-sectional restrictions on the mean returns of financial assets. These asset-pricing models are derived by restricting investors' utility functions and/or the distribution of asset returns. The primary focus in asset pricing models is on the factors which are priced in equilibrium and the risk premiums on those priced factors. Often these priced factors turn out to be economy-wide ones. On the other hand, return-generating models are statistical models which are intended to represent the stochastic process underlying the observed return series and therefore they often tend to be time-series models.

The primary objective of information content studies is to assess the economic significance of new information releases. For information content studies, the key concern is not to extract factors that are priced in equilibrium. Rather, it is to remove the components of variations in returns that are not related to the specific information event concerned (see Beaver, 1981; Ingersoll, 1987; and Chen, Copeland and Mayers, 1987). Consequently, return-generating models (such as the single-index market model) are commonly used in assessing the economic consequences of information arrivals.

For event studies with CEPIC, a careful control on industry-wide covariation is required. To the extent that industry commonalities in single-index market model residuals are not priced in equilibrium asset pricing models, the use of return-generating models are even more advantageous. As a result, return-generating models are recommended for all studies on intra-industry information transfers.

The above argument does not imply there is no relation between asset-pricing models and return-generating models. In fact, Gibbons (1982), among others, suggests that under certain conditions a test for information content can be considered as a test for asset-pricing models. Further, asset-pricing models play an important role in the specification of conditional residuals. The primary insight provided by asset-pricing models for event studies is the fact that these asset-pricing theories specify systematic returns which have to be controlled when measuring the economic consequences of firm-specific information events.

8. See Theil (1971, pp.402), Judge et al. (1985, pp.475-476) and Spanos (1986, pp.589) for further discussions on F-tests in the SUR framework.

9. See Livingston (1977, pp.871) for discussions on the relation between the proportion of explained residual variance and the proportion of total variance explained.

TABLE 1

Industries Included in the Final Sample

Index	Industry Name	SIC Code	N1	N2	N3
1	Beverages	2080	6	4	3
2	Abrasive, Asbestos, Misc Minrl	3290	5	4	3
3	Air Cond, Heating, Refrig Eq	3585	12	6	4
4	Air Transport, Scheduled	4512	15	8	6
5	Chemicals & Allied Prods	2800	11	9	9
6	Crude Petroleum & Natural Gas	1311	76	24	7
7	Eating Places	5812	25	12	5
8	Department Stores	5311	14	8	6
9	Electronic Computers	3571	16	8	5
10	Food and Kindred Products	2000	8	6	4
11	Grocery Stores	5411	15	8	4
12	Motor Vehicles & Car Bodies	3711	9	6	5
13	Paper Mills	2621	16	12	11
14	Petroleum Refining	2911	33	23	20
15	Pharmaceutical Preparations	2834	40	23	19
16	Phone Comm Ex Radiotemephone	4813	28	22	8
17	Steel Works & Blast Furnaces	3312	21	12	8
18	Motor Vehicle Part, Accessory	3714	18	8	7
19	Hotels, Motels, Tourist Courts	7011	13	7	3
20	Household Furniture	2510	8	4	3
21	Air Courier Services	4513	4	4	4
22	Aircraft	3721	6	5	5
23	Aircraft Engine, Engine Parts	3724	5	4	3

TABLE 1 (Continued)

Index	Industry Name	SIC Code	N1	N2	N3
24	Computer Storage Devices	3572	5	3	2
25	Cutlery, Hand Tools,Gen Hrdwr	3420	9	4	3
26	Photographic Equip & Suppl	3861	8	3	3
27	Newspaper: PUBG, PUBG & Print	2711	13	7	5
28	Can, Froznpresrv Fruit & Veg	2030	8	4	4
29	Grain Mill Products	2040	7	4	4
30	Tobacco Products	2100	2	2	2
31	Paperboard Mills	2631	6	5	2
32	Books: PUBG, PUBG & Printing	2731	5	4	3
33	Plastics, Resins, Elastomers	2821	10	6	4
34	Prim Smelt, Refin Nonfer Metl	3330	8	6	5
35	Prim Production of Aluminum	3334	5	5	5
36	Engines and Turbines	3510	5	5	3
37	Machine Tools, Metal Cutting	3541	5	4	3
38	Office Computing, Acctng Mach	3570	9	9	7
39	Electr, Oth Elect Eq, Ex Cmp	3600	5	4	3
40	Household Appliances	3630	4	2	2
41	Guided Missiles & Space Vehc	3760	5	5	3
42	Games, Toys,Chld Veh,Ex Dolls	3944	8	5	2
43	Drug & Proprietary Stores	5912	7	5	5
44	Television Broadcast Stations	4833	6	4	3
45	Radio,TV Broadcasting,Comm Eq	3663	14	6	4
		Total	558	329	229

N1, N2 and N3 are, respectively, the number of firms in that particular industry in the Compustat File, in the Primary Industry File and in the final sample.

TABLE 2

Distribution of the Number of Industries According to the Number of Firms

# OF FIRMS (X)	# OF INDUSTRIES(Y) FOR A GIVEN X
2	5
3	13
4	8
5	8
6	2
7	3
8	2
9	1
11	1
19	1
20	1
(Total)	45

TABLE 3

The Industry by Industry Results on Testing H_0 and H_3

H_0: No Cross-Sectional Correlation in the Market Model Residuals

H_3: No Cross-Sectional Correlation in the Two-Factor Model Residuals

Panel A: Daily Returns

Ind.	Index J	BP(MM)	H0	J*(J-1)/2	BP(2FM)	H3
1	3	65.18	1	3	38.96	1
2	3	19.77	1	3	15.98	1
3	4	15.99	1	6	15.02	1
4	6	1749.40	1	15	681.06	1
5	9	109.00	1	36	84.27	1
6	7	502.50	1	21	190.70	1
7	5	37.94	1	10	24.97	1
8	6	113.52	1	15	83.83	1
9	5	60.53	1	10	46.17	1
10	4	43.60	1	6	32.92	1
11	4	29.02	1	6	19.97	1
12	5	707.50	1	10	498.56	1
13	11	484.71	1	55	241.80	1
14	20	10243.00	1	190	2488.70	1
15	19	1066.20	1	171	470.00	1
16	8	193.33	1	28	131.44	1
17	8	307.16	1	28	173.51	1
18	7	49.49	1	21	32.72	1
19	3	36.67	1	3	23.24	1
20	3	12.05	1	3	10.78	1
21	4	27.95	1	6	24.36	1
22	5	202.05	1	10	108.72	1
23	3	4.68	0	3	4.20	0
24	2	2.33	0	1	2.33	0
25	3	10.03	1	3	6.34	0
26	3	28.97	1	3	19.79	1
27	5	138.10	1	10	87.94	1
28	4	10.58	0	6	5.25	0
29	4	34.87	1	6	12.12	0
30	2	0.06	0	1	0.06	0
31	2	8.44	1	1	8.44	1

TABLE 3, Panel A: Daily Returns (Continued)

Ind. Index	J	BP(MM)	H0	J*(J-1)/2	BP(2FM)	H3
32	3	20.88	1	3	16.97	1
33	4	13.26	1	6	8.57	0
34	5	203.46	1	10	157.32	1
35	5	450.48	1	10	238.17	1
36	3	3.18	0	3	2.62	0
37	3	13.42	1	3	10.30	1
38	7	812.79	1	21	267.62	1
39	3	125.95	1	3	93.79	1
40	2	11.22	1	1	11.22	1
41	3	0.32	0	3	0.05	0
42	2	8.35	1	1	8.35	1
43	5	58.66	1	10	36.48	1
44	3	38.13	1	3	28.71	1
45	4	15.69	1	6	12.27	0
		Total	39		Total	35

where :

Ind. Index: the industry index;
J: the number of firms in that particular industry;
J*(J-1)/2: the degree of freedom in the BP LM test;
BP(MM): the BP LM statistic for the market model;
BP(2FM): the BP LM statistic for the two-factor model;
Under H0 and H3: 1 represents rejection while 0 no rejection.

TABLE 3 (CONTINUED)
The Industry by Industry Results on Testing H_0 and H_3
H_0: No Cross-Sectional Correlation in the Market Model Residuals
H_3: No Cross-Sectional Correlation in the Two-Factor Model Residuals
Panel B: Weekly Returns

Ind. Index	J	BP(MM)	H0	J*(J-1)/2	BP(2FM)	H3
1	3	37.06	1	3	23.45	1
2	3	21.37	1	3	10.77	1
3	4	9.53	0	6	7.23	0
4	6	586.30	1	15	186.27	1
5	9	73.19	1	36	58.45	1
6	7	319.33	1	21	84.66	1
7	5	36.87	1	10	18.71	1
8	6	102.59	1	15	54.49	1
9	5	34.24	1	10	28.25	1
10	4	41.67	1	6	22.49	1
11	4	20.10	1	6	16.73	1
12	5	236.91	1	10	175.16	1
13	11	334.52	1	55	133.80	1
14	20	5047.01	1	190	845.73	1
15	19	875.06	1	171	303.94	1
16	8	176.46	1	28	100.42	1
17	8	227.83	1	28	87.76	1
18	7	32.99	1	21	29.01	0
19	3	10.65	1	3	4.95	0
20	3	8.62	1	3	6.66	0
21	4	32.48	1	6	21.72	1
22	5	121.92	1	10	50.61	1
23	3	12.51	1	3	8.94	1
24	2	0.08	0	1	0.00	0
25	3	5.31	0	3	1.45	0
26	3	10.84	1	3	4.84	0
27	5	65.25	1	10	39.65	1
28	4	22.20	1	6	13.47	1
29	4	15.85	1	6	5.22	0
30	2	3.77	0	1	3.77	0
31	2	7.58	1	1	7.58	1
32	3	7.92	1	3	5.76	0

TABLE 3, Panel B: Weekly Returns (Continued)

Ind. Index	J	BP(MM)	H0	J*(J-1)/2	BP(2FM)	H3
33	4	8.69	0	6	6.24	0
34	5	98.37	1	10	54.251	1
35	5	334.48	1	10	131.48	1
36	3	2.30	0	3	1.60	0
37	3	9.42	1	3	7.18	0
38	7	364.24	1	21	112.50	1
39	3	35.92	1	3	27.39	1
40	2	7.97	0	1	7.97	0
41	3	1.19	0	3	0.66	0
42	2	1.21	1	1	1.21	0
43	5	28.85	1	10	19.36	1
44	3	34.00	1	3	22.87	1
45	4	13.56	1	6	7.92	1
		Total	37		Total	29

where :

Ind. Index: the industry index;
J: the number of firms in that particular industry;
J*(J-1)/2: the degree of freedom in the BP LM test;
BP(MM): the BP LM statistic for the market model;
BP(2FM): the BP LM statistic for the two-factor model;
Under H0 and H3: 1 represents rejection while 0 no rejection.

TABLE 4
The Market Model
Results of Testing H_0 (No Cross-sectional Correlation)

Panel A: Daily Returns

# of industries for which H_0 is rejected:	39	86.7%
# of industries for which H_0 is accepted:	6	13.3%
Total	45	100%

Panel B: Weekly Returns

# of industries for which H_0 is rejected:	37	82.2%
# of industries for which H_0 is accepted:	8	17.8%
Total	45	100%

TABLE 5

The Industry by Industry Results on Testing H_1 and H_2

H_1: Zero-Industry Beta Hypothesis

H_2: Uniform Industry Beta Hypothesis

Panel A: Daily Returns

Ind. index	$F(H_1)$	J	$Wald(H_1)$	H1	$F(H_2)$	$Wald(H_2)$	H2
1	95.86	3	287.59	1	10.32	20.65	1
2	44.77	3	134.31	1	3.42	6.80	1
3	16.30	4	65.20	1	3.40	10.22	1
4	668.73	6	4012.40	1	10.32	51.50	1
5	38.96	9	[illegible]0.64	1	3.77	30.18	1
6	375.72	7	2630.03	1	17.54	105.26	1
7	13.12	5	65.58	1	3.05	12.18	1
8	65.90	6	395.38	1	3.55	17.75	1
9	44.22	5	221.10	1	6.87	27.48	1
10	75.73	4	302.92	1	8.68	26.05	1
11	12.02	4	48.09	1	2.30	6.92	0
12	149.75	5	748.75	1	47.50	190.05	1
13	155.68	11	1712.50	1	10.49	104.90	1
14	1140.70	20	22814.60	1	51.35	975.60	1
15	77.93	19	1480.60	1	3.90	70.44	1
16	48.65	8	389.20	1	4.70	33.13	1
17	105.50	8	844.26	1	6.01	42.01	1
18	18.41	7	128.88	1	0.69	4.14	0
19	48.07	3	144.22	1	4.56	9.12	1
20	29.82	3	89.47	1	8.69	17.39	1
21	27.85	4	111.40	1	2.88	8.64	1
22	202.50	5	1012.40	1	0.55	2.21	0
23	11.55	3	34.65	1	4.22	8.44	1

TABLE 5, Panel A: Daily Returns (Continued)

Ind.index	$F(H_1)$	J	$Wald(H_1)$	H1	$F(H_2)$	$Wald(H_2)$	H2
24	9.32	2	18.66	1	1.20	1.20	0
25	15.50	3	46.63	1	1.50	3.05	0
26	52.50	3	157.50	1	5.33	10.65	1
27	160.14	5	800.72	1	2.11	8.46	0
28	7.44	4	29.76	1	0.27	0.80	0
29	8.40	4	33.64	1	0.97	2.92	0
30	0.25	2	0.50	0	0.00	0.00	0
31	33.98	2	67.96	1	8.40	8.40	1
32	46.44	3	139.33	1	2.60	5.20	0
33	15.77	4	63.10	1	1.39	4.16	0
34	174.02	5	870.11	1	19.52	78.06	1
35	365.89	5	1829.50	1	3.83	15.32	1
36	6.95	3	20.84	1	0.23	0.46	0
37	28.10	3	84.23	1	1.11	2.22	0
38	541.00	7	3787.70	1	21.98	131.85	1
39	291.75	3	875.25	1	139.74	279.48	1
40	45.30	2	90.60	1	0.61	0.61	0
41	0.05	3	0.15	0	0.061	0.13	0
42	33.61	2	67.22	1	1.09	1.09	0
43	53.90	5	269.52	1	0.83	3.33	0
44	74.10	3	222.23	1	2.39	4.77	0
45	14.07	4	56.29	1	1.98	5.94	0

where:

J is the number of frims in the industry;

$F(H_1)$ and $Wald(H_1)$ are, respectively, the extended $F(J,J*T_d-3J)$-test nd the $Wald_{(J)}$ test statistics for the hypothesis H_1;

$F(H_2)$ and $Wald(H_2)$ are, respectively, the extended $F(J-1,J*T_d-3J)$-test and the Wald(J-1) test statistics for the hypothesis H_2;

Under H1 and H2: 1 represents rejection while 0 no rejection.

TABLE 5 (CONTINUED)
The Industry by Industry Results on Testing H_1 and H_2
H_1: Zero-Industry Beta Hypothesis
H_2: Uniform Industry Beta Hypothesis

Panel B: Weekly Returns

Ind. index	$F(H_1)$	J	$Wald(H_1)$	H1	$F(H_2)$	$Wald(H_2)$	H2
1	68.56	3	205.68	1	5.63	11.26	1
2	22.53	3	67.59	1	6.45	12.90	1
3	6.46	4	25.82	1	0.79	2.38	0
4	294.00	6	1764.00	1	2.88	14.38	1
5	18.54	9	166.88	1	1.06	8.53	0
6	229.90	7	1609.40	1	9.27	55.65	1
7	22.15	5	110.73	1	2.83	11.31	1
8	56.29	6	337.76	1	1.76	8.81	0
9	27.32	5	136.58	1	3.65	14.61	1
10	52.56	4	250.23	1	9.93	29.79	1
11	7.28	4	29.13	1	1.30	3.90	0
12	83.48	5	417.39	1	22.36	89.45	1
13	93.94	11	1033.38	1	4.90	48.98	1
14	797.68	20	1595.70	1	22.70	431.80	1
15	57.61	19	1094.66	1	2.95	53.19	1
16	38.44	8	307.50	1	2.34	16.38	1
17	101.76	8	814.10	1	3.99	27.90	1
18	10.51	7	73.58	1	0.61	3.78	0
19	6.88	3	20.66	1	0.79	1.59	0
20	19.37	3	58.12	1	6.80	13.61	1
21	163.35	4	40.84	1	5.63	16.90	1
22	126.70	5	633.65	1	2.90	11.60	1
23	23.76	3	71.30	1	12.30	24.60	1
24	0.00	2	0.00	0	0.03	0.07	0
25	0.30	3	0.89	0	0.26	0.52	0
26	11.70	3	35.11	1	1.50	2.99	0
27	70.75	5	353.74	1	0.33	1.32	0
28	25.52	4	102.10	1	0.67	2.01	0

TABLE 5, Panel B: Weekly Returns (Continued)

Ind.index	$F(H_1)$	J	$Wald(H_1)$	H1	$F(H_2)$	$Wald(H_2)$	H2
29	5.15	4	20.61	1	0.28	0.83	0
30	15.29	2	30.60	1	0.19	0.19	0
31	31.24	2	62.50	1	8.55	8.55	1
32	14.53	3	43.04	1	0.38	0.76	0
33	9.46	4	37.86	1	0.42	1.27	0
34	90.78	5	453.90	1	10.72	42.89	1
35	348.50	5	1742.60	1	1.15	4.59	0
36	2.86	3	8.58	1	0.25	0.50	0
37	19.50	3	58.50	1	0.40	0.80	0
38	242.70	7	1698.70	1	7.64	45.83	1
39	85.36	3	256.10	1	37.20	74.35	1
40	32.91	2	65.82	1	0.30	0.30	0
41	0.38	3	1.13	0	0.08	0.16	0
42	4.85	2	9.70	1	0.30	0.30	0
43	26.11	5	130.55	1	0.56	2.24	0
44	66.80	3	200.50	1	1.94	3.88	0
45	15.50	4	62.14	1	3.93	11.78	1

where:

J is the number of firms in the industry;

$F(H_1)$ and $Wald(H_1)$ are, respectively, the extended $F(J, J*T_w-3J)$-test and the Wald(J) test statistics for the hypothesis H_1;

$F(H_2)$ and $Wald(H_2)$ are, respectively, the extended $F(J-1, J*T_w-3J)$-test and the Wald(J-1) test statistics for the hypothesis H_2;

Under H1 and H2: 1 represents rejection while 0 no rejection.

TABLE 6

Two-Factor Return-Generating Model

Panel A: Results of Testing H_1 (Zero Industry Betas)

Daily Returns:		
# of industries for which H_1 is rejected	43	95.6%
# of industries for which H_1 is accepted	2	4.4%
Total	45	100%
Weekly Returns:		
# of industries for which H_1 is rejected	42	93.3%
# of industries for which H_1 is accepted	3	6.7%
Total	45	100%

Panel B: Results of Testing H_2 (Uniform Industry Betas)

Daily Returns:		
# of industries for which H_2 is rejected	26	57.8%
# of industries for which H_2 is accepted	19	42.2%
Total	45	100%
Weekly Returns:		
# of industries for which H_2 is rejected	22	48.9%
# of industries for which H_2 is accepted	23	51.1%
Total	45	100%

Panel C: Results of Testing H_3 (No Cross-Sectional Correlation)

Daily Returns:		
# of industries for which H_3 is rejected	35	77.8%
# of industries for which H_3 is accepted	10	22.2%
Total	45	100%
Weekly Returns:		
# of industries for which H_3 is rejected	29	64.4%
# of industries for which H_3 is accepted	16	35.6%
Total	45	100%

TABLE 7

The Error Components Analyses of Market Model Residuals

Panel A. Daily Returns

	Mean	Std	Max	Min
$\varsigma_{\underline{\pi}}$ (Firm-specific effects):	0%	0%	0%	0%
$\varsigma_{\underline{\phi}}$ (Time-effects):	6.7%	4.36%	16.7%	0%

Panel B. Weekly Returns

	Mean	Std	Max	Min
$\varsigma_{\underline{\pi}}$ (Firm-specific effects):	0%	0%	0%	0%
$\varsigma_{\underline{\phi}}$ (Time-effects):	11.5%	7.17%	31.6%	0%

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ON THE RATIONALITY OF VALUE LINE'S QUARTERLY EARNINGS FORECASTS

ABSTRACT: Prior research on earnings expectations has primarily focused on the accuracy of security analysts (SA) earnings forecasts and the association between the earnings forecast errors and abnormal returns. This paper argues that the evaluation of earnings expectations should be based on rationality. Two prior studies (Givoly (1985) and Abdel-khalik (1990)) on the rationality of SA earnings forecasts have provided mixed results. Rationality of multi-quarter earnings forecasts has not been examined.

This paper provides a comprehensive test of Muthian rationality of Value Line's quarterly earnings forecasts. Consideration is given to econometric issues arising from the use of overlapping data. Specifically, to detect any systematic bias in the earnings forecast errors, the hypothesis of unbiased earnings forecasts is tested at the individual firm level using Hansen's (1982) generalized method of moment procedure and White and Domowitz's (1984) least squares procedure. At the industry level, cross-sectional dependencies of earnings forecasts are examined and the unbiasedness hypothesis is tested using seemingly unrelated regressions. Next, to evaluate the efficiency of Value Line in exploiting information available, autocorrelation of forecast errors is investigated where Value Line's earnings forecasts are viewed as proxies for information available. Further, the ability of Value Line's analysts to extract information from past time-series of earnings is evaluated by testing the orthogonality of the earnings forecast errors with regard to historical earnings realizations. Finally, this paper addresses whether Value Line analysts have revised their earnings forecasts in an optimal manner. It is shown that the issue of optimal forecast revision can be formulated as a test of orthogonality of the forecast errors with regard to the forecasts issued earlier.

The main results are as follows. At the individual firm level, the primary conclusion is that the rationality of Value Line's quarterly earnings forecasts can be rejected for a majority of the firms. Value Line's quarterly earnings forecasts are biased. This paper also sheds light on the potential sources of irrationality of the forecasts. The existence of significant autocorrelation in forecast errors indicates that the rejection of rationality is at least partially due to Value Line's nonoptimal use of information available. This is supported by the evidence on Value Line's inefficient use of the information contained in the historical earnings realizations and past forecasts. These results indicate that, if the market is efficient, Value Line's earnings forecasts are not necessarily good proxies for the market's earnings expectations. More importantly, this study suggests ways in which better earnings expectations can be obtained.

At the industry level, intra-industry cross-sectional dependencies among Value Line's earnings forecasts errors are significant for the majority of the industries. This suggests that the forecast error is a function of industry-wide state variables as well as the firm-specific variables. These cross-sectional dependencies warrant the use of seemingly unrelated regressions in testing the unbiasedness hypothesis. The unbiasedness hypothesis is rejected with the seemingly unrelated regression framework for the majority of the industries.

1. Introduction

The importance of obtaining better earnings forecasts (expectations) has been well recognized in the accounting and finance literature (e.g., Brown et al. (1987a, 1987b), Watts and Zimmerman (1986)). The investment community views earnings expectations as being highly relevant for security valuations even though this viewpoint has recently been questioned on theoretical grounds (e.g., Ohlson (1990)). Many accounting and finance empirical studies also require specification of the market's earnings expectations which are unobservable. Proxies used by researchers include the earnings forecasts generated by univariate time series models and security analysts forecasts of earnings. SA forecasts seem to be the preferred surrogates: the superiority of SA earnings forecasts is suggested by two findings. First, SA earnings forecasts are more accurate (e.g., Brown and Rozeff (1978), Brown et al. (1987a), and Conroy and Harris (1987)). Second, several studies (e.g., Foster (1977), Fried and Givoly (1982), and Brown et al. (1987b)) have provided evidence that SA earnings forecast errors are more strongly associated with abnormal stock returns than the earnings forecasts errors of univariate time-series models, though O'Brien (1988) obtains opposite results.

The preceding approaches to the evaluation of SA earnings forecasts appear ad hoc. In earlier studies, SA earnings forecast accuracy was often evaluated by pooling cross-sectional and time-series forecast errors and was measured by an error metric such as mean absolute relative error. This approach to forecast accuracy evaluation has been criticized by, among others, Brown, Foster and Noreen (1985, p. 120-123), and O'Brien (1988). The choice of the error metric is arbitrary. When these error metrics are pooled across firms and over time to obtain a grand measure of accuracy, cross-section dependencies and autocorrelations are ignored. This aggregation may lead to invalid statistical inferences (O'Brien (1988), p.34). Further, the grand measure of accuracy may not be able to detect some systematic errors in SA's earnings forecasts (Givoly (1985), p.376). More importantly, the accuracy studies have ignored other important properties of rational expectations such as whether SA can use their information efficiently (Abdel-khalik (1990), p.144). Studies focusing on the association between SA forecast errors and abnormal stock returns fail to specify a theoretical link between the association and rationality of the forecasts (see Ohlson (1990), p.649 for similar comments on the relation between accounting variables and security prices); that is, a stronger association does not necessarily suggest rationality. For example, forecast error _a_ may be more contemporaneously correlated with the abnormal returns than the forecast error _b_, forecast error _b_ may have a much smaller conditional variance and therefore could be a more rational forecast than forecast error _a_. In fact, the result in O'Brien (1988) that time-series model earnings forecasts produced stronger association between forecast errors and residual returns than analysts' forecasts provides empirical support for the inappropriateness of the association approach to earnings forecast evaluation.

This study proposes that SA earnings forecasts should be evaluated according to their rationality. The rationality approach is superior for the following reasons. First, there is a well-developed theory of rational expectations in the economics and finance literature (see Begg (1982), Mishkin (1983), and Sheffrin (1983) for reviews). Second, appropriate econometric methods have been developed to address the empirical implications of rational expectations (see Mishkin (1983), Lovell (1986), Maddala (1988) and Baillie (1989) for discussions on issues involved in testing rationality). Finally, the results from testing rationality suggest ways to produce better expectations.

The purpose of this paper is to test the rationality of Value

Line's quarterly earnings forecasts. Value Line's earnings forecasts are systematically evaluated by addressing the following question: are SA earnings forecasts rational? For each firm in the sample, the unbiasedness of the earnings forecasts is evaluated, autocorrelation of the forecast errors is examined, and the orthogonality condition with regard to the information contained in the past earnings realizations is tested. Further, the issue of optimality of SA forecast revisions is addressed in the rationality framework.

At the industry level, the cross-sectional dependencies in Value Line's earnings forecasts are examined and the unbiasedness hypothesis is tested within the framework of seemingly unrelated regression (SUR).

The paper proceeds as follows. Section 2 discusses the concept of rational expectations and tests for rationality. Data and sample issues are explained section 3. Section 4 presents results and interpretations. Section 5 summarizes the paper.

2. The Concept of Rational Expectations and Tests for Rationality

2.1. The concept of rational expectations and its empirical implications

In his pathbreaking paper, Muth (1961) suggests that economic agents' subjective expectations are rational if the expectations are equal to the conditional expectations of the variables.

Let $X_{j,k,t}$ be Firm j's actual earnings for k-quarter ahead from the current time point t and $F_{j,k,t}$ be the k-quarter ahead earnings forecast for Firm j issued at time t. That is, $F_{j,k,t} = E(X_{j,k,t}|I_t)$ where I_t is the market's information set at the time of forecast (t). Let $e_{j,k,t}$ be the k-step ahead forecast error and then $e_{j,k,t} = X_{j,k,t} - F_{j,k,t}$.

The expectation $F_{j,k,t}$ is said to be fully rational if all relevant information at the time of forming the forecasts is utilized in an optimal manner. That is, for $F_{j,k,t} = E(X_{j,k,t}|I_t)$, if no other unbiased predictor has smaller variance than $F_{j,k,t}$, then the forecast $F_{j,k,t}$ is said to be fully rational.

The concept of rationality should not be confused with the concept of completeness (as emphasized by Brown and Maital (1981)). A forecast is said to be complete if all the relevant information is used, but not necessarily in an optimal manner. Full rationality implies completeness, but completeness does not imply full rationality.

Because the information set of the market is not observable, the concept of partial rationality (see Sargent (1973)) is often used in empirical work. A forecast is partially rational with regard to a proper subset S_t of the market information set I_t if $F_{j,k,t} = E(X_{j,k,t}|S_t)$. Partial rationality is necessary but not sufficient for full rationality.

Partial rationality has several testable empirical implications.

(1) Partial rationality implies unbiasedness; that is, the expectation of the forecast error conditional on S_t should be zero, $E(e_{j,i,t}|S_t)=0$. For the regression equations,

$X_{j,k,t} = a_{j,k} + b_{j,k} F_{j,k,t} + u_{j,k,t}$, unbiasedness implies that

$a_{j,k} = 0$ and $b_{j,k} = 1$ (the unbiasedness hypothesis H_1).

(2) Partial rationality imposes restrictions on the autocorrelation structure of forecast errors. Overlapping data problems arise whenever the forecast horizon k exceeds the observation interval which is one quarter for actual quarterly earnings realizations. Overlapping data are often used to make more efficient use of information.

It has been shown by, among others, Hansen and Hodrick (1980), Brown and Maital (1981), and Hayashi and Sims (1983), that k-step ahead forecast errors will follow a moving average (MA) process of order k-1 due to this overlapping data problem. Therefore, for one-step ahead forecasts, partial rationality requires the absence of autocorrelation in forecast errors. However, this "no autocorrelation" conclusion does not apply to multi-step ahead (k>1) forecasts where the forecast horizon (k=2,3,...) exceeds the observation interval. That is, existence of autocorrelation in multi-step (k>1) forecast error series does not necessarily imply the rejection of rationality. Nevertheless, partial rationality does impose restrictions on the structure of autocorrelation of multi-step forecasts. Specifically, the order of autocorrelation of k-step ahead forecast errors cannot exceed k-1.

In this paper, the hypothesis of no serial correlations (efficiency hypothesis H_2) $E(e_{j,k,t}|e_{j,k,t-i})=0$ (where i>k-1) is tested respectively for k=1,2,3,4. Specifically, the regression equations $e_{j,k,t} = q_{j,k,0} + q_{j,k,1}\, e_{j,k,t-k} + q_{j,k,2}\, e_{j,k,t-k-1} + q_{j,k,3}\, e_{j,k,t-k-2} + q_{j,k,4}\, e_{j,k,t-k-3} + s_{j,k,t}$ are estimated and H_2 is evaluated by testing the hypothesis:

$q_{j,k,0} = q_{j,k,1} = q_{j,k,2} = q_{j,k,3} = q_{j,k,4} = 0$.

The rejection of efficiency hypothesis (H_2) implies that SA have not made an optimal use of all the information available to them at the time of producing forecasts. Therefore, the rejection of H_2 naturally gives rise to the question of which variables in SA's information set

S_t have not been exploited optimally.

(3) Partial rationality requires that the forecast errors $e_{j,k,t}$ be orthogonal to each and every component (subset) of the information set S_t. The forecast errors should be orthogonal to any variable (information) in the information set S_t. That is, $E(X_{j,i,t} - F_{j,i,t}) | S_t) = 0$. This is often called the orthogonality condition.

In the case of SA earnings forecasts, the observable variables in S_t are, among others, the past series of actual earnings and historical series of SA forecasts. The orthogonality condition with regard to past earnings (H_3) is examined by estimating the regression equation: $e_{j,k,t} = c_{j,k,0} + c_{j,k,1} X_{j,t-1} + c_{j,k,2} X_{j,t-2} + c_{j,k,3} X_{j,t-3} + c_{j,k,4} X_{j,t-4} + v_{j,k,t}$ and then testing H_3: $c_{j,k,0} = c_{j,k,1} = c_{j,k,2} = c_{j,k,3} = c_{j,k,4} = 0$.

The orthogonality condition with regard to the past SA forecasts can be considered as an issue of optimal forecast revision. If the forecast revisions are rational, then the forecast errors should be orthogonal to the forecasts issued earlier. This optimal forecast revision hypothesis (H_4) is evaluated in the regression equation: $e_{j,k,t} = d_{j,k,0} + d_{j,k,1} F_{j,k+1,t-1} + d_{j,k,2} F_{j,k+2,t-2} + d_{j,k,3} F_{j,k+3,t-3} + w_{j,k,t}$ by testing H_4: $d_{j,k,0} = d_{j,k,1} = d_{j,k,2} = d_{j,k,3} = 0$.

At the industry level, the following SUR model is estimated for each k and for each industry in the sample. $X_{n,k,t} = \alpha_{n,k} + \beta_{n,k} F_{n,k,t} + f_{n,k,t}$ where $n=1,2,\ldots,N$ which is the number of firms in the industry and $t=1,2,\ldots,40$: i.e. 40 quarters over a ten-year period. The hypothesis of no cross-sectional correlation (H_5) in the earnings forecasts is tested using Breusch and Pagan's (1980) Lagrange multiplier (LM) statistic. For industries where cross-sectional dependencies are significant, the unbiasedness hypothesis H_1 is retested within the framework of SUR.

3.2. Econometric issues in testing rationality

As discussed above, the use of overlapping data (for k>1) can induce serial correlation in the regression equation, $X_{j,k,t} = a_{j,k} + b_{j,k} F_{j,k,t} + u_{j,k,t}$. This warrants careful econometric considerations for both estimation and inference.

It is well-known that in the presence of autocorrelations, OLS will provide consistent estimates of regression coefficients but produce biased and inconsistent estimates of the covariance matrix and therefore make the inference invalid. Normally, autocorrelation problems can be dealt with through the use of feasible generalized least squares (FGLS); however, the application of FGLS to time series regressions requires the regressors to be strictly exogenous (i.e. $E(u_{j,k,t} | F_{j,k,t-1}, F_{j,k,t}, F_{j,k,t+1}, F_{j,k,t+2}, F_{j,k,t+3}, \ldots) = 0$) (see Hansen and Hodrick (1980) and Cumby, et al. (1983) for further comments). This condition implies that knowing the future earnings realizations should not improve the current forecasts for $X_{j,k,t}$. This is obviously violated in the case of SA earnings forecasts. Therefore, the FGLS will yield inconsistent estimates of the covariance matrix (see Hansen (1982), Hansen and Sargent (1982)) since the independent variable $F_{j,k,t}$ is predetermined (weakly exogenous but not strictly exogenous).

In case of SA earnings forecasts, weak exogeneity ($E(F_{j,k,t} u_{j,k,t}) = 0$) implies that OLS's point estimates of regression coefficients are consistent. Accordingly, in this paper, OLS are applied to estimate the regression coefficients. However, valid inference requires a consistent estimate of the covariance matrix of the regression parameters. Two methods are applied to obtain consistent estimates of the coefficient covariance matrix: Hansen's (1982) generalized method of moments (GMM) estimator and White and Domowitz's (1984) least squares (LS) estimator. Both methods are general enough to allow for either or both of autocorrelation and heteroskedasticity. Further, both the GMM and LS procedures can be easily implemented as they do not require an explicit correction for autocorrelation and heteroskedasticity.

In the economics literature, the GMM procedure has been applied to test rationality (e.g. MacDonald and Torrance (1990), and Rich (1990)). Hansen's GMM method has been recently applied in the finance literature (e.g., Chang and Huang (1990), Lim (1990), Longstaff (1989), Mark (1988), and Stambaugh (1988)).

Because the sample covariance matrix estimate as specified in Hansen (1982) may not be positive semidefinite in finite samples, Newey and West's (1987) algorithm for estimating the covariance matrix is used.

White and Domowitz's (1984) LS procedure can be considered as a time-series equivalent to White's (1980) cross-sectional heteroskedasticity-consistent covariance estimator.

2.3. Review of Testing the rationality of SA earnings forecasts

Studies in two accounting research areas have indirectly indicated the irrationality of SA's earnings forecasts. First, prior research has shown that SA's earnings forecasts tend to be overly optimistic (e.g., Fried and Givoly (1982), O'Brien (1988), Chatfield (1989) and De Bont and Thaler (1990)). The existence of systematic bias implies irrationality. A second line of research studied the optimality of combining earnings forecasts from univariate time-series models with SA's earnings forecasts. These studies indicated that combination of SA's forecasts with forecasts generated from time-series model of earnings can outperform SA's earnings forecasts (e.g., Conroy and Harris (1987), Newbold *et al*. (1987), Guerard (1989), and Lobo and Nair (1990)). This finding suggests that SA's earnings forecasts do not make an optimal use of information in the past time-series of earnings and therefore are irrational.

Two studies, Givoly (1985) and Abdel-khalik (1990), have directly addressed the issue of rationality of SA earnings forecasts. Using a time-series approach, Givoly (1985) examined the rationality of annual earnings forecasts obtained from the S&P's Earnings Forecaster for the period from 1969 to 1979. Specifically, Givoly tested the unbiased hypothesis and investigated the orthogonality of forecast errors to the information contained in the time series and the cross-sectional properties of past earnings per share. Further, Givoly investigated the serial correlation of the forecast errors. Givoly concluded that the annual earnings forecasts are rational.

Recently, through a cross-sectional analysis, Abdel-khalik (1990) tested the rationality of one-quarter ahead earnings forecasts issued by Value Line. Abdel-khalik (1990) suggested that, while Value Line's one-quarter ahead earnings forecasts are unbiased, they are not orthogonal to the information contained in the stock prices and therefore are not rational.

By definition, the rational expectations hypothesis imposes restrictions on the time-series properties of the forecast series. Therefore, in testing rationality, time series regressions are a preferred choice to the cross-sectional approach (as argued in Givoly (1985)). Some implications of rationality, such as the efficiency hypothesis H_2, can only be tested in a time-series regression framework. The use of annual data means fewer observations (11 time-series observations in Givoly's study), which should be a concern given the fact that the statistics are asymptotic. The use of quarterly data should give more powerful and reliable tests of rationality.

Thus it seems that Givoly (1985) and Abdel-khalik (1990) have provided mixed evidence on the rationality of SA earnings forecasts. The rationality of multi-quarter earnings forecasts has not been examined.

Testing rationality also relates to accounting research on the information advantage of SA relative to univariate time-series models in forecasting earnings. The extant research has suggested that SA may have used a broader information set than just past earnings (e.g Brown et al. (1987a), and Brown, Richardson and Schwager (1987)). From the perspective of rationality, this only implies that SA forecasts are more complete but not necessarily rational. The concept of rationality suggests that one forecast is better than another (issued at the same time point, so there is no timing advantage) because of an information advantage (i.e. more complete) and an efficiency advantage (i.e. more efficient use of existing information) or both. Tests for rationality allow the researcher to discriminate between the information advantage and the efficiency advantage.

3. Data and Sample Issues

The earnings forecasts and actual quarterly earnings are collected from The Value Line Investment Survey. Because tests in this study involve the examination of the autocorrelation structure of forecast errors, a longer time series of earnings forecasts and actual quarterly earnings series is required. Further, this implies that the tests in this study are applicable to one-step, two-step, three-step and four-step ahead earnings forecasts for which Value line provides complete time series coverage. The sample covers a ten year period of 1980 to 1989, which provides 40 quarterly observations.

In order to evaluate the intra-industry contemporaneous correlation among SA earnings forecast errors, firms in the following seven industries are included in the initial sample: aerospace, rubber and tire, airline, car manufacturing, auto parts, precision instruments, and retail. Firms with less than complete coverage for the entire sample period by The Value Line Survey are excluded from the sample. This results in a sample of 51 firms in the seven industries. The names of the 51 firms are listed in Appendix 1.

Further, for any firm in the sample, an earnings forecast series is excluded if there are missing observations in the series. For example, if there are any missing observations in one-step ahead forecast series of Firm A, then the one-step ahead forecast series of Firm A is dropped. The final sample consists of 36, 51, 46 and 39 time series for, respectively, one-, two-, three- and four-quarter ahead forecasts. To be consistent with actual earnings series, Value Line's earnings forecasts are adjusted for significant changes in the number of shares outstanding.

On average, the sampled firms tend to be very large. Further, the sample has a survivorship bias. The results have to be interpreted with these limitations in mind.

4. Results and Interpretations

4.1. On the unbiasedness of Value Line's earnings forecasts

The regression equations $X_{j,k,t} = a_{j,k} + b_{j,k} F_{j,k,t} + u_{j,k,t}$ are estimated for k=1,2,3,4 respectively by OLS, White and Domowitz's (1984) LS estimator, and Hansen's (1982) GMM estimator. OLS results are reported to illustrate the importance of considering econometric issues.

Table 1 presents the results of testing the hypothesis H_1: $a_{j,k} = 0$ and $b_{j,k} = 1$. Panel a of Table 1 provides the results under OLS. The unbiasedness hypothesis is rejected for 15 out of the 36 firms (i.e. 42 percent) for one-quarter ahead (k=1), 29 out of the 51 (57 percent) for two-quarter ahead (k=2), 29 out of the 46 (63 percent) for three-quarter ahead (k=3), and 27 out of the 39 (69 percent) for four-quarter ahead (k=4) forecasts.

Panel b of Table 1 presents the results of testing the unbiasedness hypothesis (for k=2,3,4) under White and Domowitz's (1984) autocorrelation-consistent and heteroskedastic consistent covariance estimator. The unbiasedness hypothesis is rejected for 27 out of the 51 firms (53 percent) for two-quarter ahead, 24 out of the 41 (58.5 percent) for three-quarter ahead (where the procedure failed for five firms), and 23 out of the 36 (64 percent) for four-quarter ahead forecasts (where the procedure failed for three firms).

The results of testing H_1 using the GMM procedure are reported in Panel c of Table 1. The rejection ratios are respectively 48 out of the 50 firms (94.1 percent) for two-step ahead forecasts, 42 out of the 46 firms (95.2 percent) for three-step ahead forecasts and 34 out of the 39 firms (94.9 percent) for four-step ahead forecasts. The results in Panel c provide a much stronger support for the rejection of the unbiasedness hypothesis than the ones presented in Panel a and Panel b.

Two conclusions can be drawn. First, even though the results differ across the inference methods, the majority of the multi-quarter earnings forecasts provided by Value Line are biased under all the methods. Second, one-step forecasts are least biased in terms of the proportion of rejecting hypothesis H_1. This proportion of rejection increases with the time horizon of the earnings forecasts under OLS and White and Domowitz's (1984) LS procedure. That is, a larger proportion of Value Line's earnings forecasts become biased as the forecast horizon gets longer. However, this trend is not observed under Hansen's GMM method.

The results on testing the unbiasedness hypothesis H_1, while consistent with findings in Fried and Givoly (1982), O'Brien (1988), Chatfield (1989), and De Bont and Thaler (1990), are different from the one obtained by Abdel-khalik (1990), who provides evidence that Value Line's earnings forecasts are on average unbiased. This difference may be a reflection of the different econometric approaches used in the two studies. While Abdel-khalik (1990) uses cross-sectional analysis on the pooled cross-sectional and time-series data, this study tests H_1 through time-series regressions. Abdel-khalik does not account for autocorrelation in both estimation and inferences. Further, Abdel-khalik only examines first-step ahead forecasts which are less biased than multi-quarter ahead forecasts.

Tests on the direction of the bias have been conducted using OLS. The results are consistent with the finding in the literature (see e.g., Fried and Givoly (1982), O'Brien (1988), and De Bont and Thaler (1990)). That is, if Value Line's earnings forecasts are biased at all, they tend to be overly optimistic. Due to the overlapping data problem, this paper's finding on the direction of the bias has to be interpreted with caution.

4.2. On the autocorrelation of forecast residuals

The forecast residuals are examined for any significant autocorrelations that are inconsistent with the implications of rationality. The regression equations:

$e_{j,k,t} = q_{k,0} + q_{k,1}\ e_{j,k,t-k} + q_{k,2}\ e_{j,k,t-k-1} + q_{k,3}\ e_{j,k,t-k-2} + q_{k,4}\ e_{j,k,t-k-3} + s_{j,k,t}$ are estimated and the hypothesis H_2:

$q_{k,0} = q_{k,1} = q_{k,2} = q_{k,3} = q_{k,4} = 0$ are tested under OLS and Pagan's (1974) LS procedure which takes autocorrelation into account in both estimation and inferences. The results are presented in the Table 2.

Panel a presents the results under OLS. H_2 is rejected for eight out of the 36 firms (22.2 percent) for one-quarter ahead, 20 out of the 51 (39.2 percent) for two-quarter ahead, 16 out of the 46 (34.8 percent) for three-quarter ahead, and 13 out of the 39 (33.3 percent) for four-quarter ahead forecast errors.

The findings under Pagan's (1974) LS with AR(4) errors are shown in Panel b. H_2 is rejected for 26 out of the 36 firms (i.e. 72.2 percent) for one-quarter ahead, 41 out of the 51 (80.4 percent) for two-quarter ahead, 31 out of the 46 (67.4 percent) for three-quarter ahead, and 19 out of the 39 (48.7 percent) for four-quarter ahead forecast errors.

The results suggest the existence of significant autocorrelation in Value Line's forecast errors. This implies that Value Line analysts have not exploited all the information available to them at the time point of forecasts. That is, not all the information in S_t has been used optimally in producing the earnings forecasts. This raises another question: which information subset in information set S_t has not be used optimally by Value Line?

4.3. On the orthogonality hypothesis

Abdel-khalik (1990) indicates that Value Line has not exploited all the information in stock prices in generating its earnings forecasts. This study examines an even weaker condition: whether Value Line has optimally used the information in historical earnings realizations and forecasts issued earlier by Value line. That is, the orthogonality of forecast errors with regard to the information contained in the historical earnings series and past forecasts is investigated.

H_3 is tested by regressing Value Line's forecast residuals on the most recent four quarterly earnings realizations. The regression equations are estimated by Pagan's (1974) LS procedure respectively with MA(4) errors and AR(4) errors. The test results are presented in Table 3.

Under Pagan's procedure with MA(4) errors (Panel a), H_3 is rejected for 19 out of the 36 firms (52.8 percent) for one-quarter ahead, 34 out of the 51 (67 percent) for two-quarter ahead, 32 out of the 46 (69.6 percent) for three-quarter ahead, and 22 out of the 39 (56.4 percent) for four-quarter ahead forecast errors.

Similar evidence is obtained under Pagan's procedure with MA(4) errors (see Panel b). H_3 is rejected for 29 out of the 36 firms (80.6 percent) for one-quarter ahead, 40 out of the 51 (78.4 percent) for two-quarter ahead, 36 out of the 46 (78.3 percent) for three-quarter ahead, and 29 out of the 39 (74.4 percent) for four-quarter ahead forecast errors.

These results suggest that Value Line's earnings forecasts have not optimally exploited the information contained in the historical earnings realizations. The findings are consistent with the results in Newbold et al. (1987), Guerard (1989), Lee and Chen (1990), and Lobo and Nair (1990) where they indicate that combinations of statistical forecasts from time series models of earnings and SA earnings forecasts can improve forecast accuracy. The rejection of H_3 is one of the reasons why Value Line's forecasts errors are autocorrelated.

The issue of optimal forecast revisions (H_4) can only be addressed for k=1,2,3. For each k, the regression equation is estimated by Pagan's procedure respectively with MA(4) and AR(4) errors. Table 4 shows the results of testing H_4. Under the assumption of AR(4) errors (see Panel a), H_4 is rejected for 19 out of the 36 firms (52.8 percent) for one-quarter ahead, 22 out of the 46 (47.8 percent) for two-quarter ahead, 20 out of the 39 (51.3 percent) for three-quarter ahead forecasts. Under MA(4), H_4 is rejected for 24 out of the 36 firms (66.7%) for one-quarter ahead, 27 out of the 46 firms (58.7%) for two-quarter ahead, 23 out of the 39 firms (56%) for three-quarter ahead forecasts.

In summary, Table 4 indicates that Value Line's quarterly earnings forecasts are not optimally revised with the arrival of new information. This is another reason for the rejection of efficiency hypothesis H_2. This suggests that Value Line's forecast accuracy can be improved upon by utilizing the information available to them.

4.4. Analyses at the industry level

The results of testing hypothesis H_5 (no intra-industry cross-sectional dependence in forecast errors) are reported in Table 5. Panel a provides detailed results on a industry by industry basis. Summaries are shown in Panel b.

Cross-sectional dependence is not a problem for one-step ahead forecasts. This suggests that the forecast errors in one-step ahead forecasts are primarily a result of firm-specific factors. For two-step, three-step and four-step ahead forecasts, cross-sectional dependence is significant for over 85 percent of the industries. This indicates that the forecast errors in two-step, three-step and four-step ahead forecasts are correlated due to the unexpected industry-wide factors. The existence of significant contemporaneous correlations among forecast errors of firms in the same industry suggests that Value Line's forecast errors cannot be directly pooled together without taking into account such cross-sectional dependencies. This is one factor that may account for the difference between the results in this study and the findings of Abdel-khalik (1990).

Table 6 shows the results of testing the unbiasedness hypothesis H_1 within the SUR framework. Panel a presents the results for each industry. Panel b provides summaries of the test results. Rejection rates are respectively 4 out of 6 (or 66.7%), 7 out of 7 (or 100%), 6 out of 7 (85.7%), and 6 out of 7 (85.7%) for one-quarter, two-quarter, three-quarter and four-quarter ahead earnings forecasts. This is consistent with the findings obtained by using time-series regressions for individual firms.

5. Summary and Conclusions

This study tests the rationality of Value Line's multi-quarter earnings forecasts. Specifically, three major properties of a rational orecast are examined: unbiasedness, autocorrelation of forecast errors and the orthogonality condition. The major results follow.

Value Line's quarterly earnings forecasts are on average biased. Further, this bias tends to increase as the forecast horizon gets longer. This result is consistent with some of the prior studies such as Fried and Givoly (1982), O'Brien (1988), and De Bont and Thaler (1990) and is contradictory to the finding by Abdel-khalik (1990).

A second major finding is that Value Line's earnings forecasts errors are significantly autocorrelated. This suggests that Value Line did not exploit all the information available. That is, Value Line could have utilized its existing information to generate better forecasts. An explanation for the existence of autocorrelations is that Value Line's analysts were not able to adjust their earnings forecasts quickly to the structural changes in the firms being forecast. This slow learning process on the part of Value Line can introduce autocorrelations and/or nonstationarity in the forecast errors.

Because the information set available to Value Line is not known to the researcher, a weak orthogonality condition is examined. Specifically, the question addressed is whether Value Line has exploited all the information in the past earnings realizations and earlier forecasts issued by Value Line. Surprisingly, for the majority of the firms, both the orthogonality condition and the optimal forecast revision condition are rejected. This implies that the information contained in the past earnings realizations and past forecasts can be used to improve Value Line's earnings forecasts. The systematic bias in SA's earnings forecasts and the rejection of orthogonality conditions tend to confirm the findings in the behavioral literature that the use of heuristics by SA can introduce bias and result in an inefficient use of information (see Ashton (1982), and Affleck-Graves et al. (1990)).

The results also suggest ways in which better expectations of earnings might be produced. An analyst's superiority in forecasting earnings can be achieved by any combination of the following two factors: an information (or completeness) advantage (due to a broader information set) and an efficiency advantage (due to more efficient use of available information).

Finally, cross-sectional dependence in the forecast errors is examined. No significant cross-sectional dependence is found in one-step ahead earnings forecasts for any of the sampled industries. However, cross-sectional dependence is significant in two-step, three-step, and four-step ahead earnings forecasts for six out of seven industries. This implies that the sources and nature of SA earnings forecast errors may depend on the forecast horizon.

For researchers, the results indicate that Value Line's earnings forecasts are not necessarily good proxies for the market's expectations of earnings. Therefore, a search for alternative proxies is warranted.

For practitioners, the results imply that Value Line's earnings forecasts can be improved upon. One way to proceed is to make more efficient use of available information. Further, the existence of significant cross-sectional dependencies suggests that Value Line earnings forecasts may be improved by exploiting such a dependence.

Future research could consider the rationality evaluation of analysts' consensus earnings forecasts such as the ones provided by Lynch, Jones and Ryan's Institutional Brokers Estimate System (IBES) and Zacks Investment Research's Icarus Service. Further, the combining of time series model forecasts and analysts' forecasts warrants more research.

APPENDIX 1: SAMPLED COMPANY AND INDUSTRY NAMES

#1 AEROSPACE INDUSTRY
BOEING COMPANY
ESYSTEMS INC.
GENERAL DYNAMICS
GRUMMAN
LOCKHEAD CORP
MARTIN MARIETTA
MCDONNEL DOUGLAS
NORTHROP CORP.
ROCKWELL INT'L.
ROHR
SUNDSTRAND CORP
TRW INC.
#2 RUBBER AND TIRE INDUSTRY
BANDAG INC.
CARLISLE CORP.
COOPER TIRE & RUBBER
GOODYEAR TIRE
#3 AIRLINE INDUSTRY
AMERICAN AIRLINE
AIRBORNE FREIGHT
DELTA AIRLINES
FEDERAL EXPRESS
KLM ROYAL DUTCH
PAN AMERICAN
SOUTHWEST AIRLINES
US AIR INC.
#4 CAR MANUFACTURER INDUSTRY
CHRYSLER CORP
FORD MOTOR
GENERAL MOTOR
PACCAR INC.
#5 AUTO PARTS INDUSTRY
ALLEN GROUP
ECHLIN MFG. CO.
FEDERAL-MOGUL
GENUINE PARTS CO.
STD. MOTOR PROD.
#6 PRECISION INSTRUMENTS INDUSTRY
EG&G
ESTERLINE CORP.
FISCHER & PORTER CO.
KOLLMORGEN
PERKIN-ELMER
POLARROID CORP.
RECOGNITION EQUIP'T
TALLEY IND.
#7 RETAIL INDUSTRY
ALEXANDER'S
CARTER HAWLEY HALE
DAYTON HUDSON
JAMESWAY CORP.
KMART CORP.
MAY DEPT. STORES
MERCANTILE STORES
NORDSTROM INC..
PENNY (J.C.)
SEARS ROEBUCK&CO
WOOLWORTH (F.W.)

Table 1: **Results of Testing H1 (Unbiasedness Hypothesis)**

The regression equation: $X_{j,k,t} = a_{j,k} + b_{j,k} F_{j,k,t} + u_{j,k,t}$

The hypothesis H1 (for each k): $a_{j,k} = 0$ and $b_{j,k} = 1$

Panel a: OLS

# of steps ahead (k)	1	2	3	4
# of firms available	36	51	46	39
# of firms where H1 is rejected	15	29	29	27
The proportion of rejection	42%	57%	63%	69%

Panel b: White and Domowitz's procedure

# of steps ahead (k)	1	2	3	4
# of firms available	36	51	41	36
# of firms where H1 is rejected	15	27	24	23
The proportion of rejection	42%	53%	58.5%	64%

Panel c: Hansen's procedure

# of steps ahead (k)	1	2	3	4
# of firms available	36	51	46	39
# of firms where H1 is rejected	15	48	42	34
The proportion of rejection	42%	94%	91.3%	87.2%

Table 2: Results of Testing H2 (Efficiency Hypothesis):

The regression equation:

$$e_{j,k,t} = q_{j,k,0} + q_{j,k,1}\, e_{j,k,t-k} + q_{j,k,2}\, e_{j,k,t-k-1} + q_{j,k,3}\, e_{j,k,t-k-2} + q_{j,k,4}\, e_{j,k,t-k-3} + s_{j,k,t}$$

The hypothesis H2: $q_{j,k,0} = q_{j,k,1} = q_{j,k,2} = q_{j,k,3} = q_{j,k,4} = 0$.

Panel a: OLS

# of steps ahead (k):	1	2	3	4
# of firms available	36	51	49	39
# of firms for which H2 is rejected	8	20	16	13
The proportion of rejection	22.2%	39.2%	34.8%	33.3%

Panel b: Pagan's LS procedure with AR(4) errors

# of steps ahead (k):	1	2	3	4
# of firms available	36	51	49	39
# of firms for which H2 is rejected	26	41	31	19
The proportion of rejection	72.2%	80.4%	67.4%	48.7%

Table 3: Results of Testing H3 (Orthogonality Condition)

The regression equation:

$$e_{j,k,t} = c_{j,k,0} + c_{j,k,1} X_{j,t-1} + c_{j,k,2} X_{j,t-2} + c_{j,k,3} X_{j,t-3} + c_{j,k,4} X_{j,t-4} + v_{j,k,t}$$

The hypothesis H3: $c_{j,k,0} = c_{j,k,1} = c_{j,k,2} = c_{j,k,3} = c_{j,k,4} = 0$.

Panel a: Pagan's procedure with AR(4) errors

# of steps ahead (k)	1	2	3	4
# of firms available	36	51	46	39
# of firms for which H3 is rejected	19	34	32	22
The proportion of rejection	52.8%	67%	69.6%	56.4%

Panel b: Pagan's procedure with MA(4) errors

# of steps ahead (k)	1	2	3	4
# available	36	51	46	39
for which H3 is rejected	29	40	36	29
T. ortion of rejection	80.6%	78.4%	78.3%	74.4%

Table 4: Results of Testing H4 (Optimal Forecast Revision Condition)

The regression equation:

(1) For one-step ahead forecast errors (k=1)
$e_{j,1,t} = d_{j,1,0} + d_{j,1,1} F_{j,2,t-1} + d_{j,1,2} F_{j,3,t-2} + d_{j,1,3} F_{j,4,t-3} + w_{j,1,t}$

The hypothesis H4 (k=1): $d_{j,1,0} = d_{j,1,1} = d_{j,1,2} = d_{j,1,3} = 0$.

(2) For two-step ahead forecast errors (k=2)
$e_{j,2,t} = d_{j,2,0} + d_{j,2,1} F_{j,3,t-1} + d_{j,2,2} F_{j,4,t-2} + w_{j,2,t}$

The hypothesis H4 (k=2): $d_{j,2,0} = d_{j,2,1} = d_{j,2,2} = 0$.

(3) For three-step ahead forecast errors (k=3)$e_{j,3,t} = d_{j,3,0} + d_{j,3,1} F_{j,4,t-1} + w_{j,2,t}$

The hypothesis H4 (k=3): $d_{j,3,0} = d_{j,3,1} = 0$.

Panel a: Pagan's procedure with AR(4)

# of steps ahead (k)	1	2	3
# of firms applicable	36	46	39
# of firms for which H4 is rejected	19	22	20
The proportion of rejection	52.8%	47.8%	51.3%

Panel b: Pagan's procedure with [illegible]

# of steps ahead (k)	1	2	3
# of firms applicable	36	46	39
# of firms for which H4 is rejected	24	27	23
The proportion of rejection	66.7%	58.7%	56%

Table 5: Results of Testing H5: (No Cross-sectional dependence)

Panel a:

	# Of steps ahead			
Industry index	1	2	3	4
1	N	Y	Y	Y
2	N	Y	Y	Y
3	N	N	N	Y
4	N	Y	Y	Y
5	N	Y	Y	Y
6	N	Y	Y	N
7	0	Y	Y	Y

Y: REJECTION
N: NO REJECTION
0: NOT APPLICABLE

Panel b:

# of steps ahead	1	2	3	4
# of industries available	6	7	7	7
# of industries for which H5 is rejected	0	6	6	6
The proportion	0	85.7%	85.7%	85.7%

Table 6: Results of Testing H1 (SUR)

The SUR equations: $X_{n,k,t} = \alpha_{n,k} + \beta_{n,k} F_{n,k,t} + f_{n,k,t}$ Where n=1,2,...,N

Panel a: Industry-by-industry results of testing H1 (SUR)

	# Of steps ahead			
Industry index	1	2	3	4
1	Y	Y	Y	Y
2	N	Y	Y	Y
3	Y	Y	N	Y
4	Y	Y	Y	Y
5	N	Y	Y	Y
6	Y	Y	Y	N
7	0	Y	Y	Y

Y: REJECTION
N: NO REJECTION
0: NOT APPLICABLE

Panel b: Summarized results of testing H1 (SUR)

# of steps ahead	1	2	3	4
# of industries available	6	7	7	7
# of industries for which H1 is rejected	4	7	6	6
The proportion of rejection	66.7%	100%	85.7%	85.7%

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