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AND CAPITAL MARKET EQUILIBRIUM

By

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ABSTRACT

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This research investigates the relationship between security returns and replacement cost disclosures mandated by the Securities and Exchange Commission's Accounting Series Release 190. In this regard, other recent replacement cost studies have focused solely on the market's initial reaction to these disclosures. Accordingly, they were limited to the use of historical cost data and Value Line estimates of replacement cost in deriving expectations. Furthermore, these investigations were done in isolation, i.e., their information hypotheses pertain only to replacement cost variables. As a result, their research designs could not provide evidence regarding the Commission's contention that replacement cost data provide user information not otherwise available.

To correct for the first limitation, a firm's 1976 replacement cost data are used in formulating the market's 1977 expectation of current cost income. Deviations from each firm's actual 1977 replacement cost income then form realizations of that information variable. To overcome the second limitation, the historical cost income forecast error variable is included so that portfolio returns are conditioned on various realizations of both variables. This inclusion provides a mechanism for determining whether the current cost income numbers reflect information beyond that reflected by the historical cost income numbers.

One hundred and eight firms are used to construct six information portfolios. Each are conditioned on the various realizations of the two income forecast error variables. Exploiting the properties of the capital asset pricing model, pre-experimental equivalence is assumed to be attained. Thus, detection of significant return differences implies that the forecast error realizations (signals) reflect information. The use of two conditioning variables necessitates an examination of the relationship between them since it is crucial to appropriate design selection and interpretation of test results.

The inferred variable relationship resulted in a one-factor design being selected and reparameterization of its underlying model resulted in the *a priori* contrasts of interest. *A priori* contrasts are employed since they eliminate the need for control portfolios (unconditional portfolio returns) and increase the power of the test. Included are specific contrasts which test the primary research hypothesis that current cost income signals do not reflect information beyond that of the historical cost income signals. The test period consists of the fifty work weeks subsequent to the March 31, 1977 portfolio formation date. The results are consistent with the hypothesis stated above and, therefore, provide evidence that required replacement cost disclosures provide no information to the market.

D E D I C A T I O N

To the Professor, and all like him,
may their efforts be appreciated on
earth as I am sure they are in heaven.

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ABBREVIATIONS

ANOVA	Analysis of variance
ASR	Accounting Series Release
CAPM	Capital asset pricing model
COP	Current operating profit
COPFE	Current operating profit forecast error
CRSP	Center for Research in Security Prices
DOF	Distributable operating flow
ECCI	Expected current cost income
EEI	Expected economic income
FAS	Financial Accounting Standard
GLM	General linear model
GLRM	General linear return model
HCI	Historical cost income
HCIFE	Historical cost income forecast error
MANOVA	Multivariate analysis of variance
PCCI	Past current cost income
PEI	Past economic income
RCS	Realizable cost savings
R'edCS	Realized cost savings
SEC	Securities and Exchange Commission
SIC	Standard Industrial Classification
UCOP	Unexpected current operating profit
UEI	Unexpected economic income

CHAPTER I

INTRODUCTION AND OVERVIEW

The Securities and Exchange Commission's No. 190 (ASR 190) requiring particular firms to disclose certain replacement cost (current cost) data was issued March 23, 1976. This requirement is effective for fiscal years ending on/or after December 25, 1976. The purpose of this study is to examine the information content of these required replacement cost data. Specifically, the purpose is to examine the relationship between current cost data and security returns, i.e., to investigate the extent to which these disclosures reflect information pertinent to assessing firms' equilibrium prices (hereafter, called expected returns).

ASR 190 required that certain large registrants disclose the estimated current replacement cost of inventories and productive capacity and the approximate cost of sales and depreciation based on replacement cost. Having imposed this requirement, the Commission recognized that the firms might incur non-trivial costs in obtaining, storing, and reporting this data. Research by O'Connor and Chandra [1977, pp. 166-167] supports this possibility. Although the initial reaction to the requirement by the business community was overwhelmingly negative (see O'Connor [1977, pp. 37-42]), the commission was adamant in its conviction that the benefits to be derived from such disclosures would exceed the costs. In arriving at its decision the Commission stated its belief ". . . that such data are important and useful to investors and are not otherwise obtainable." The Commission further states:

> . . .that under current economic conditions, data about the impact of changes in the prices of specific goods and services on business firms is of great significance to investors in developing an understanding of any firm. While the current general rate of inflation has been reduced from 1974 levels, it is still at a level such that

unsupplemented historical cost based data do not adequately reflect current business economics.

If the Securities and Exchange Commission (SEC) is to continue requiring disclosure, it is reasonable to expect evidence suggesting that investors use this data. Now that a limited amount of data have been made available, it would be appropriate to empirically investigate whether investors behave as if their assessed distribution of securities' future values are formed conditionally on this data.

With the Financial Accounting Standards Board's adoption of the Statement of Financial Accounting Standards No. 33 (FAS No. 33), ASR 190 was rescinded in favor of FAS No. 33. FAS No. 33 requires particular firms to disclose certain current cost data in their published annual reports. Thus, while ASR 190 is technically revoked the replacement cost requirement is not. There are, however, reporting requirement differences between FAS No. 33 and ASR 190. The fundamental difference between the two is their definition of current cost. FAS No. 33 defines current cost as the cost of acquiring the existing processes of production at todays prices, whereas ASR 190 defines current cost as the cost currently required to replace existing processes with currently available technology. It follows that changes in technology could cause a difference in the two information sets.

If, however, one assumes that there exists no material difference between the two information sets, then the results of this study could be used in evaluating the information content of FAS No. 33's current cost disclosure requirements. On the other hand, if one assumes there is a difference, then this research would still be valuable. Evidence on the information content of both requirements would be needed to make comparative evaluations. Research results could imply that the

ASR 190 required data reflect information, whereas FAS No. 33 do not. It is reasonable to expect that evaluation of all evidence could have an impact on future current cost reporting requirements.

Previous research studies regarding replacement cost disclosures have shown no significant evidence of an information effect. However, all of these studies focused on the market's initial reaction to these disclosures. Accordingly derivation of their replacement cost expectation models were limited to the use of historical cost data and Value Line estimates of replacement costs which were announced prior to the 10-K filings.

This study differs from these studies in two important ways. First, it uses prior reported replacement cost data in forming the market's expectation of current cost income. Secondly, it incorporates the historical cost income variable as well as the current cost income variable to analyze the security return behavior of firms. This, in turn, provides a mechanism for determining whether the current cost income numbers reflect information beyond that reflected by the historical cost income numbers.

Regarding these two variables, Gonedes [1978, p. 27] incorporating the concepts espoused by Spence [1974] states that:

> Taken by itself, a signal is effective if agents behave as if their assessed distributions of securities' future values are formed conditionally on the signal (or a perfect substitute for it).

Reported income numbers and, in particular, current cost income numbers may be effective signals. This would occur if these numbers reflect information about attributes of firms' production, investment, and financing decisions (e.g., distribution functions of cash flows) deemed important by investors.

Prior to ASR 190 reported income numbers were derived primarily from historical cost data. For disclosing firms, however, required disclosures of current cost data now enable investors to derive income numbers based on current cost data (i.e., cost of sales and depreciation). Furthermore, this additional data allows investors to disaggregate historical cost income (HCI) into (using the terminology employed by Edwards and Bell [1961]) current operating profit (COP) and realized cost savings (R'edCS). This disaggregation of the HCI would ideally correspond to the operating and holding activities of the firm. The COP concept, defined as the difference between revenue and current cost of assets used to create that revenue, attempts to measure the firm's current period operating efficiency. The R'edCS concept, defined as the difference between current cost and historical cost of assets used during a period, attempts to measure the contribution to total income from the firm's holding activities realized during the period. Since the HCI concept does not provide measures which distinguish between these two income producing activities, current cost advocates have contended that the HCI concept does not provide unambiguous signals about attributes of firms' decisions (Edwards and Bell [1961, pp. 10-11, 223-227]).

Given certain assumptions, Revsine [1970] contends that COP is a surrogate for expected economic income. Expected economic income is the difference between the beginning and end of period values of discounted expected future cash flows as envisioned at the beginning of the period. An equivalent formulation defines expected economic income as the product of the discount rate and the initial discounted value. Most valuation models that are derived from partial equilibrium theories of asset valuation under both certainty and uncertainty are variants of the expected economic income model.[1] Within the context of these models, accounting measures which provide information about changes in expected cash flows from operations would be useful. Thus, the COP potential to approximate expected economic income supports the contention that replacement cost data may provide information useful to investors that is not already reflected in the HCI number.

This study consists of eight chapters. Chapter II introduces the theoretical foundation underlying the study's experimental design and hypotheses. Specifically, information content is defined, implications of market efficiency are explained, properties of the two-parameter, two-factor capital asset pricing model are exploited, an income expectation model is introduced and the assumed distribution properties of security returns and their resultant implications are explored.

A comparative analysis of the econometric properties of the residual return and the difference in total returns metrics is presented in Chapter III. In addition, the general linear design model from extant statistical theory is introduced and its equivalence with the two-factor (zero-beta) model is derived. This design model is subsequently used to facilitate metric comparison in the general case and to formulate the contrasts to be tested.

Chapter IV reviews the theoretical rationale set forth in the literature which has explained why replacement cost data should provide useful information to market agents in making their investment decisions. The primary methodological distinction between this study and other recent replacement cost studies, along with a brief summary of their findings, is also presented.

Chapter V presents criteria used in selecting firms, describes the processes employed to derive income forecast errors and weekly returns, and explains procedures in constructing information portfolios. The beta estimation and test periods are set forth. In addition, issues of external and internal validity are addressed.

Statement of the omnibus hypothesis is presented in Chapter VI. Moreover, the specific hypotheses comprising the omnibus hypothesis are set forth and interpreted for both the two-factor and one-factor (fixed effects) design cases. The relationship between the two income forecast error variables regarding appropriate design choice is analyzed.

Empirical findings are presented in Chapter VII and Chapter VIII concludes by summarizing the key aspects of the study and by making recommendations for future research.

FOOTNOTE TO CHAPTER I

[1]Hayes [1978] relates the economic income model with a representative model from valuation theory.

CHAPTER II

THEORETICAL FOUNDATIONS

Overview

The primary purpose of this study is to examine the relationship between reported replacement cost data and security returns. An equivalent formulation of the purpose is to determine if the current replacement cost data has information content within the context of the capital markets. It is this latter statement of the purpose that will be used as a framework for testing the hypotheses addressed in this study.

Let $\tilde{R}$ be a random variable.[1] Let $\tilde{\theta}$ be another random variable (or vector of random variables). Information theory defines $\tilde{\theta}$ as having information content, if for some realization, θ of $\tilde{\theta}$, the conditional distribution $F(\tilde{R}/\theta)$ is not identical to the unconditional distribution $F(\tilde{R})$ (see Spence [1974, pp. 7-10] and Demski [1971, p. 14]). If, on the other hand, $F(\tilde{R}/\theta) = F(\tilde{R})$ for all realizations, θ of $\tilde{\theta}$, then $\tilde{\theta}$ does not have information content. Accordingly, agents do not behave as if values of $\tilde{\theta}$ affect their probabilistic assessment of $\tilde{R}$.

Reported accounting numbers are random variables $\tilde{\theta}$, whereas their realizations represent accounting events θ. Inferences can be made about the information content of these accounting numbers by observing the behavior of some (dependent) random variable $\tilde{R}$ during a period in which it is reasonable to expect that the event may be related to this random variable. Therefore, it is necessary to determine three criteria: the event, the random variable, and the time period. The event to be considered in this study is the value of the income forecast error. The random variable to be observed is the return on a security (or a portfolio of securities).

Previous research has provided evidence that indicates that an association exists between reported accounting numbers and security returns (e.g., Ball and Brown [1968], Beaver [1968] and Beaver and Dukes [1972]). The implication is that accounting numbers will have information content if either or both of the following two conditions exists: (1) the market uses these numbers in setting prices or (2) these numbers are associated with other sources of information used by the market in setting prices. Under the first condition there exists both correlation and causality between accounting numbers and stock returns, whereas under the second condition, only correlation exists. These two conditions along with the assumption that the market is efficient with respect to publicly available information will be used to identify a time period that one would expect to capture any potential information effects. Market efficiency implies that the market adjusts prices fully and instantaneously when new information becomes available (see Fama [1970]). It is assumed in this study that the market is efficient with respect to publicly available information.

With respect to market efficiency, and condition (1), one should expect a market reaction immediately following public disclosure of the accounting event. If, on the other hand, condition (2) exists, one might expect a market reaction prior to public disclosure of the accounting event. This would occur whenever the other source of information used by the market becomes publicly available prior to disclosure of the accounting event. The findings of previous research noted above, suggests that other sources of information that are reflected in accounting numbers impound in stock returns several months before public disclosure of these numbers. In summary, it appears that the appropriate time period should include both periods immediately following and preceding the disclosure of the accounting event.

These three criteria have been discussed within the context of information theory and the semi-strong form of market efficiency. Assuming that the distribution function F is normal, then one condition necessary for inferring information content is that $E(\tilde{R}/\theta) \neq E(R)$. However, to analyze conditional and unconditional expected return behavior of securities (or portfolios), it is necessary to make an assumption as to how equilibrium prices (or expected returns) are established by the market.

The two-parameter, two-factor capital asset pricing model (CAPM) provides an equilibrium expectation of the return from holding an asset. The model is a two-parameter model in the sense that the joint distribution of returns is assumed to be multivariate normal. This distribution is defined by two parameters, the vector of means and the variance-covariance matrix. The model is a two-factor model in the sense that the dependent variable, expected return, is a function of two independent variables. The model implies that there exists a linear relationship between an asset's return and its systematic risk. Jensen [1972] provides a review of theory and evidence supporting the various forms of the model. His assumptions of the model are adopted here. The Sharpe-Lintner version of this model is given by the expression

$$(2\text{-}1) \quad E(\tilde{R}_{it}) = R_{ft} + \beta_{it}[E(\tilde{R}_{mt}) - R_{ft}],$$

where

$\tilde{R}_{it}$ = the return on a security (or portfolio) i in period t,

R_{ft} = the risk free rate of return in period t,

β_{it} = the measure of systematic risk for security (or portfolio) i in period t, and

$\tilde{R}_{mt}$ = the return on the market in period t.

Within an efficient market, values of the model's respective parameters are established, conditioned on the information available at time t. Since the only parameter unique to asset i is beta β_{it}, the expected returns of any two assets, i and j, are to be treated as equal, given that their betas are equal. In other words, if $\beta_{it} = \beta_{jt}$, then $E(\tilde{R}_{it}) = E(\tilde{R}_{jt})$ because R_{ft} and $E(\tilde{R}_{mt})$ are constant for all assets during a given t. Gonedes [1975, p. 224, 1978, pp. 48-49] contends it is this property of the Sharpe-Litner model that enables one to control "other things" so that an assessment can be made of the information content of a random variable $\tilde{\theta}$. The following discussion of its main facets will provide the rationale for its use in detecting information content.

Omitting the subscript t for convenience, let portfolio p be a portfolio consisting of only firms that report the realization, θ of $\tilde{\theta}$, after establishing equilibrium at time t. In contrast, let portfolio r consist of randomly selected securities. Consequently, portfolio r is not formed conditionally on any realization of $\tilde{\theta}$. Furthermore, suppose that both portfolios are constructed such that $\beta_p = \beta_r$. If $\tilde{\theta}$ does not have information content beyond that available when equilibrium was established at time t, then the two-parameter model implies that $E(\tilde{R}_p/\theta) = E(\tilde{R}_r)$. On the other hand, if these expected returns were unequal then $\tilde{\theta}$ must have information content. This is because all "other things" which might effect the expected returns are held constant by setting $\beta_p = \beta_r$.

Expectation Models

Examining the information content of replacement cost data, the particular attribute considered is the income forecast error. The methodology employed will analyze the security return behavior of firms conditioned on different realizations of both their historical cost income (HCI) and current operating profit (COP) forecast errors. These two accounting random variables are denoted by $\tilde{\theta}_1$ and $\tilde{\theta}_2$, respectively, and are the components of the 2 x 1 "information" vector of random variables $\tilde{\theta} = (\tilde{\theta}_1, \tilde{\theta}_2)$.

In calculating realized values of these two forecast error variables, it is necessary to specify an investor expectation model. All conclusions are conditioned on the propriety of the model(s) assumed. Other researchers have attempted to garner stronger support for their conclusions by incorporating in their studies a number of expectation models (e.g., Beaver and Dukes [1972, pp. 322-324]). However, in choosing an expectation model for calculating the COP forecast error values, the available data limit the selection to the martingale model. Fortunately, there is some theoretical support (to be discussed below) for using this model to calculate the COP forecast error realizations.

The martingale model is given by

$$\text{(2-2)} \quad \tilde{y}_{t+1} = y_t + \delta + \tilde{u}_{t+1},$$

where

$$E(\tilde{u}_{t+1}/u_t, u_{t-1}, \ldots) = 0.$$

The drift factor δ may equal zero. This model is less restrictive than the random walk model since the u_t residual series does not have to be independently and identically distributed.

The results of previous empirical research has suggested that given only the past values of the HCI sequence, the martingale model is a descriptively valid expectation model of future expected HCI (Ball and Watts [1972]). This evidence is consistent with the statement that the

HCI forecast error reflects information about a firm's value when the martingale model is used as a surrogate for investor's income expectation (e.g., Ball and Brown [1968] and Gonedes [1978]). Within the framework of the martingale model, Gonedes [1978, p.37] has argued that some other signal (e.g., the COP forecast error) which becomes available when the HCI number is realized may reflect information if that signal alters the expected values of the HCI predictive distributions for future periods. His contention supports the use of the martingale model to investigate the COP forecast error.

The martingale model will be used in this study to derive both COP and HCI forecast errors. Applying this model to the COP variable, data limitations prevent the statistical calculation of the drift factor δ, and will therefore be assumed to be zero. There is, however, under both the opposing assumptions of stability and instability some theoretical support for using this period COP as the best estimate of the following period's COP.

In the case where stability is assumed, Edwards and Bell [1961, p. 99] state:

> The significance of current operating profit may extend to periods other than the current period if certain assumpstions are valid. Current operating profit can be used for predictive purposes if the existing production process and the existing conditions under which that process is carried out are expected to continue into the future; current operating profit then indicates the amount that the firm can expect to make in each period over the long run.

Under the instability assumption Revsine [1973, p. 127] states:

> In an environment in which relative prices, risk, the technological processes are constantly changing, one can seldom make very accurate estimates of future current operating profits. Furthermore, when changes in operating variables have no discernable pattern, detailed trend analyses are of limited benefit. For lack of a better method, a reasonable basis for estimating future flows is to extrapolate the most recent periods' results under the assumption that no further

changes will occur. If indeed, no further changes occur (and if volume is constant), then the following period's current operating profit will be equal to the present period's current operating profit.

Ideally, one attempts to use the expectation model that reflects aggregate market behavior. When constructed and tested, most (if not all) expectation models become public information. Assuming the semi-strong form of the efficient market hypothesis, a researcher might further assume that the expectation model that "best" predicts is the one used by market agents. However, at this point in time, there exists a limited amount of data for specifying COP expectation models because of the recency of Securities and Exchange Commission (SEC) reporting standards requiring this information. Therefore, in addition to the above theoretical arguments, it seems reasonable to expect that market agents act as if they use the martingale model.

The Distribution Properties, Assumptions, and Implications of Security Returns

The weak-form of the efficient market hypothesis implies that a security's returns (i.e., price changes over uniform intervals) are independent. If, in addition, one assumes that a security's returns are drawings from the same population, then returns are independently and identically distributed.

The simple return for a period (interval) involves the product of simple returns for each of the intermediate sub-intervals. By taking the logarithmic function of one plus the simple return, this expression is transformed into the logarithmic return and is referred to as the return with continuous compounding. This return is also independently and identically distributed. However, unlike the simple return for a period, this return is equal to the sum of logarithmic returns for each of the intermediate periods. Consequently, some financial theorists have argued through the use of the central limit theorem that this distribution approximates normality if the variance is finite and the number of subperiods is large (Fama [1976, pp. 17-20]). Furthermore, the continuously compounded return expressed as $\ln(1 + \tilde{R}_t)$ is approximately equal to the simple return $\tilde{R}_t$ where $\tilde{R}_t$ is less than 15% in absolute value (Fama [1976, p. 20]). This reasoning has provided the theoretical rationale for hypothesizing a normal distribution for a security's return.

The empirical results provided by Fama [1976, pp. 21-38] imply that both daily and monthly returns are leptokurtic relative to normal distributions. These distributions are members of the symmetric stable family of distributions of which the normal distribution is a member. However, unlike the normal distribution they have infinite variances. The degree of leptokurtosis detected in monthly returns is less pronounced than that of daily returns. In fact, their departures from normality are not sufficient enough to completely invalidate the normal assumption.

A sufficient, but not necessary condition for the theoretical construction of the CAPM is that the joint distribution of security returns is multivariate normal.[2] Therefore, at this level, departures from normality are not an impediment for using the model. Accordingly, this study will employ the equilibrium property derived from those versions of the model which assume that the market is a minimum variance portfolio (Fama [1976, pp. 301-302 and pp. 320-370]). Specifically, if $\beta_i = \beta_j$, then $E(\tilde{R}_i) = E(\tilde{R}_j)$. Hereafter, this property will be referred to as the equilibrium assumption. Although one could choose not to employ this assumption and/or the CAPM, both provide a theoretical rationale for constructing sample portfolios with pre-experimental equivalence.[3]

With respect to a variant of the CAPM for conditional returns, this equivalence provides the means for eliminating from total returns that systematic portion attributable to economy-wide events (see (3-25)). The remaining variation can then be dichotomized into two parts. The first part, the remaining systematic variation in the data, is assumed to be accounted for by fixed effects in the model. The second part, the remaining random variation, is assumed to arise from small independent influences which produce normally distributed residuals.

Consequently, it is the joint distribution properties of these residuals or equivalently the associated conditional returns which are of primary concern to the researcher. This joint distribution is assumed to be multivariate normal. It differs from the assumption that the unconditional returns are jointly distributed multivariate normal. In other words, the normality (or lack of it) of one distribution does not imply the normality of the other. Furthermore, neither assumption is less restrictive than the assumption that the joint distribution, which includes the returns and the conditioning variable(s), is multivariate normal.

An important point not to be overlooked is that probability statements in tests of significance refer to the sampling distribution of the statistic and not to the distribution of observed conditional returns. Of course, if the joint distribution of the conditional returns is multivariate normal, then the statistic's distribution will be multivariate normal. However, if the joint distribution is not multivariate normal, the central limit theorem (assuming finite variance) implies that the distribution of the statistic is essentially multivariate normal for large sample sizes (see Rao [1965, p. 108]).

Currently, there is no practical method available for determining whether a sample is drawn from a multivariate normal population (Bock [1975, p. 155]). However, one necessary condition is that the marginal distributions are univariate normal. The evidence cited above regarding monthly returns is not sufficient to reject the hypothesis that they are normally distributed and thus the multivariate assumption. Therefore, both joint conditional and unconditional distributions are assumed to be multivariate normal.

FOOTNOTES TO CHAPTER II

[1]Tilde (~) denotes a random variable.

[2]Fama [1971] shows that any probalistic distribution which is a member of the symmetric stable class with characteristic exponent a > 1 is sufficient for the theoretical construction of the CAPM.

[3]Without invoking this assumption, one could use the market model to derive a residual return metric. Employing this metric, construction of sample portfolios with pre-experimental equivalence is also possible. The market model and the residual metric are discussed in Chapter III.

CHAPTER III

COMPARISON OF RETURN METRICS AND MODEL EQUIVALENCE

The Information Hypothesis

Financial accounting research involved with studying relationships between accounting data and security returns (hereafter referred to as market based research) has employed two different return metrics. They will be referred to as (1) the residual return metric and (2) the difference in total returns metric. Metric terminology was introduced by Beaver [1980] to differentiate between types of return measures and their underlying distribution functions. Thus, comparison of the econometric properties of different return metrics is equivalent to comparing each of the functions' corresponding parameters. To facilitate comparison, all conditional and unconditional returns will assumed to be distributed multivariate normal.

Both of these metrics are derivations of the most fundamental of return metrics, i.e., the total return. This metric is defined as the percentage change in price for a period after adjusting for dividends. In symbols, it is expressed as

$$(3\text{-}1) \quad \tilde{R}_{zt} = \frac{\tilde{P}_{zt} + \tilde{D}_{zt} - P_{zt-1}}{P_{zt-1}} ,$$

where

$\tilde{R}_{zt}$ = the total return for security z during period t,

$\tilde{P}_{zt}$ = the price of security z at the end of period t,

$\tilde{D}_{zt}$ = dividends paid during period t, and

P_{zt-1} = the price of security z at the end of period t-1.

The comparison will be made in the context of expected returns,[1] which has been the primary focus of most previous studies. In this context, a researcher interested in testing the information content of an accounting random variable $\tilde{\theta}$ would investigate the expected conditional return, given some realization (signal) θ of $\tilde{\theta}$. This expected conditional return is then compared to the expected unconditional return. The complete statement of both null and alternative hypothesis is

$$(3\text{-}2) \quad H_0: \; E(\tilde{R}_{zt}/\theta_{zt}) - E(\tilde{R}_{zt}) = 0 \text{ for all realizations of } \tilde{\theta}_{zt}, \text{ and}$$

$$(3\text{-}2') \quad H_1: \; E(\tilde{R}_{zt}/\theta_{zt}) - E(\tilde{R}_{zt}) \neq 0 \text{ for at least one realization of } \tilde{\theta}_{zt}.$$

An equivalent formulation of the null and alternative hypotheses discussed by Gonedes [1975, p. 222] is given by

$$(3\text{-}3) \quad H_0: \; E(\tilde{R}_{zt}/\theta_{izt}) - E(\tilde{R}_{zt}/\theta_{jzt}) = 0 \text{ for all } i \text{ and } j,\ i \neq j, \text{ and}$$

$$(3\text{-}3') \quad H_1: \; H_0 \text{ is false.}$$

Both sets require a test of the equivalence of means. The number of realizations of $\tilde{\theta}$ determines the number of means. Thus, subsequent reference to the n realization case will imply a test of the equality of n means.

Beaver [1980] explored the characteristics of each metric's mean and variance parameters. His comparative analysis was made in the context of analyzing a single realization of the conditioning variable $\tilde{\theta}$. The conclusion he reached in this setting is that both metrics have the same expected values, however, the form of their variances differ. Specifically, they are $\sigma^2(\tilde{\varepsilon}_{pt})$ and $\sigma^2(\tilde{\varepsilon}_{pt}) + \sigma^2(\tilde{\varepsilon}_{qt}) - 2\text{Cov}(\tilde{\varepsilon}_{pt},\tilde{\varepsilon}_{qt})$

where p and q represent two different securities (portfolios). Therefore, the size of one in relation to the other depends on the value of the correlation coefficient associated with the latter.

For example, if the disturbance terms (residuals) $\tilde{\varepsilon}_p$ and $\tilde{\varepsilon}_q$ are uncorrelated, then $Cov(\tilde{\varepsilon}_p,\tilde{\varepsilon}_q) = 0$ and the variance term $\sigma^2(\tilde{\varepsilon}_p)$ would be the smaller of the two. However, Beaver acknowledges that one can not exclude the non-existence of interdependence (cross sectional correlation) between disturbance terms. Assuming that the security return process is generated by a single factor (the market return) and no omitted variables exist, Fama [1976, p. 74] shows mathematically the interdependence of security residuals and provides empirical evidence consistent with this phenomenon ([pp. 351-355]). Gonedes [1978, pp. 54-57] provides evidence that portfolio residuals are also correlated.

Existence of large positive correlation could make the latter variance term the smaller of the two. Thus, Beaver considers this aspect of his comparative analysis important since along with Type I error rate and sample size, the magnitude of the variance affects the power of a test (Slakter [1972, p. 273]). Consequently, the choice of a metric could have an impact on actual test results.

Although a researcher may choose to investigate the effect of only one realization, a random variable must have at least two realizations. It will be shown that by employing the appropriate statistical testing procedure in cases involving all realizations of $\tilde{\theta}$, the residual return metric approach is transformed into the difference in residual returns metric approach. Furthermore, the distribution parameters of both difference in returns metric approaches are identical.

In cases including all realizations of $\tilde{\theta}$, three alternative procedures are available for testing the omnibus null hypothesis: (1) make n independent tests comparing each conditional return with the unconditional return; (2) use a joint test of the equality of means incorporating, if necessary, _post hoc_ contrasts as an adjunct procedure; (3) use a joint test of the equality of means with _a priori_ contrasts.[2]

The primary disadvantage of alternative (1) is that multiple independent tests "inflate" the total probability of making a Type I error. In general, the probability of accepting all the null hypotheses using n independent tests when in fact they are all true is

$$(3\text{-}4) \qquad \prod_{k=1}^{n} (1 - \alpha_k).$$

Thus, the probability of rejecting at least one of the null hypotheses when in fact they are all true is

$$(3\text{-}5) \qquad \alpha^* = 1 - \prod_{k=1}^{n} (1 - \alpha_k) \ ,$$

where α^* is the total probability of making a Type I error for the collective hypothesis set (Bock [1975, p. 190]).

For example, in the case with two tests, if $\alpha_1 = \alpha_2 = .05$, then $\alpha^* = .0975$. On the other hand, if the researcher selects a total Type I error rate of .05, then $\alpha_1 = \alpha_2 \cong .025$ for each test. Reducing the α level reduces the power of a test (Slakter [1972, p. 273]) and the difference between α_k and α^* is the price a researcher would pay for following this approach.

Joint testing procedures called for in alternatives (2) and (3) control the overall Type I error rate. Under both of these alternatives, if the joint test of the omnibus null hypothesis is rejected, then subsequent testing to detect the cause of this rejection is usually desired.

The advantage of using a priori contrasts for detecting causes is that they provide more powerful tests than post hoc contrasts (Bock [1975, pp. 266-267]).

From the viewpoint of maximizing the power of all tests, the third alternative is preferable. It is this procedure that will be used as a standard to provide a testing framework in the comparison of return metrics.

The Market Model

The earliest studies in market based research employed the residual return metric. Researchers originally used the market model in deriving this metric and it will be introduced here.

The discussion will be presented in a conceptual setting involving only one asset and time period. Therefore, asset and time subscripts will be omitted. The market model is expressed as

$$(3\text{-}6)\qquad \tilde{R} = \alpha + \beta\tilde{R}_m + \tilde{\varepsilon} \ ,$$

where

$\tilde{R}_m$ = the return of a market index for period t,

α,β = the intercept and slope parameters, and

$\tilde{\varepsilon}$ = the disturbance term.

With the assumption that returns are distributed multivariate normal, then $E(\tilde{\varepsilon}) = 0$, and $\tilde{\varepsilon}$ and $\tilde{R}_m$ are independent. The expected value and variance are, respectively,

$$(3\text{-}7)\qquad E(\tilde{R}) = \alpha + \beta E(\tilde{R}_m), \text{ and}$$

$$(3\text{-}8) \quad \mathrm{Var}(\tilde{R}) = \beta^2\sigma^2(\tilde{R}_m) + \sigma^2(\tilde{\varepsilon}).$$

The conditional return given some realization θ_i of $\tilde{\theta}$ is expressed as

$$(3\text{-}9) \quad (\tilde{R}/\theta_i) = \alpha + \beta\tilde{R}_m + (\tilde{\varepsilon}/\theta_i)$$

$$= \alpha + \beta\tilde{R}_m + \gamma_i + \tilde{e}_i ,$$

where $\tilde{R}_m$ and $\tilde{\theta}$ are assumed to be independent. Thus, given an actual realization θ_i of $\tilde{\theta}$ implies the fixed effect parameter γ_i. This version of the model for conditional returns differs from the usual presentation only in that it decomposes the residual random variable into two components. They are the expected value (i.e., $E(\tilde{\varepsilon}/\theta_i) = \gamma_i$) and a disturbance random variable $\tilde{e}_i$, where $E(\tilde{e}_i) = 0$.

The conditioning variable $\tilde{\theta}$ is generally assumed to be an ordinal scale variable (see e.g., Gonedes [1978] and Beaver [1980]), therefore, an equivalent formulation could be developed employing dummy variables. Assuming n possible realizations of $\tilde{\theta}$, the market model could be expanded as

$$(3\text{-}10) \quad \tilde{R} = \alpha + \beta\tilde{R}_m + \gamma_1\tilde{X}_1 + \gamma_2\tilde{X}_2 + \cdots + \gamma_n\tilde{X}_n + \tilde{\varepsilon},$$

where each variable $\tilde{X}_i$ assumes the value one when θ_i is realized and zero otherwise. Moreover, their respective coefficients are the fixed effect parameters.

Under both the unconditional and conditional versions of the model, the term $\alpha + \beta\tilde{R}_m$ is assumed to reflect economy-wide events, whereas, terms $\tilde{\varepsilon}$ and $(\gamma_i + \tilde{e}_i)$ reflect firm-specific events. Both the residual return and difference in total returns metrics will be described using the version introduced here.

Residual Return Metric

A researcher concerned with the information content of $\tilde{\theta}$ might employ a residual return metric and reformulate the information hypothesis given by (3-2) and (3-3) in terms of residual returns. The market model can be used to derive this metric. However, unlike the market model, the total return is conditioned on a realization of $\tilde{R}_m$. In addition, if a realization θ_i of $\tilde{\theta}$ is given, then the metric is expressed as

$$(3\text{-}11)\quad (\tilde{\varepsilon}/R_m,\theta_i) = (\tilde{R}/R_m,\theta_i) - \alpha - \beta R_m = \gamma_i + \tilde{e}_i.$$

In words, the metric is the difference between the total return and that portion attributable to economy-wide events. The expected value and variance are, respectively,

$$(3\text{-}12)\quad E(\tilde{\varepsilon}/R_m,\theta_i) = \gamma_i + E(\tilde{e}_i) = \gamma_i\text{, and}$$

$$(3\text{-}13)\quad Var(\tilde{\varepsilon}/R_m,\theta_i) = \sigma^2(\tilde{e}_i).$$

The reason for its construction is to eliminate from the total return variability attributable to $\tilde{R}_m$ (see (3-8)).

Difference in Total Returns Metric

In contrast, a researcher concerned with eliminating variability attributable to R_m might employ a metric as the difference in total returns. This metric can be expressed as

$$\begin{aligned}(3\text{-}14)\quad \tilde{d}_i &= (\tilde{R}/\theta_i) - \tilde{R} \\ &= (\alpha + \beta\tilde{R}_m + \gamma_i + \tilde{e}_i) - (\alpha + \beta\tilde{R}_m + \tilde{\varepsilon}) \\ &= \gamma_i + \tilde{e}_i - \tilde{\varepsilon}\ .\end{aligned}$$

The expected value and variance are, respectively,

(3-15) $E(\tilde{d}_i) = \gamma_i + E(\tilde{e}_i) - E(\tilde{\varepsilon}) = \gamma_i$, and

(3-16) $\mathrm{Var}(\tilde{d}_i) = \sigma^2(\tilde{e}_i) + \sigma^2(\tilde{\varepsilon}) - 2\mathrm{Cov}(\tilde{e}_i, \tilde{\varepsilon})$.

In comparing the two metrics the results are the same as Beaver's. That is, the expected returns are the same but the variances differ. However, Beaver was analyzing only one realization of $\tilde{\theta}$, therefore, he used the assets unconditional return in constructing the difference in total returns. Alternatively, if one takes the difference between two conditional returns, then the properties of the difference in total returns metric change. For example, let θ_i and θ_j be two realizations of $\tilde{\theta}$, then

$$
\begin{aligned}
(3\text{-}17) \quad \tilde{d}_{i,j} &= (\tilde{R}/\theta_i) - (\tilde{R}/\theta_j) \\
&= (\alpha + \beta\tilde{R}_m + \gamma_i + \tilde{e}_i) - (\alpha + \beta\tilde{R}_m + \gamma_j + \tilde{e}_j) \\
&= \gamma_i - \gamma_j + \tilde{e}_i - \tilde{e}_j .
\end{aligned}
$$

The expected value and variance are, respectively,

(3-18) $E(\tilde{d}_{i,j}) = \gamma_i - \gamma_j + E(\tilde{e}_i) - E(\tilde{e}_j) = \gamma_i - \gamma_j$, and

(3-19) $\mathrm{Var}(\tilde{d}_{i,j}) = \sigma^2(\tilde{e}_i) = \sigma^2(\tilde{e}_j) - 2\mathrm{Cov}(\tilde{e}_i, \tilde{e}_j)$.

The form of the variance terms in (3-16) and (3-19) are the same. However, in comparing (3-15) and (3-18) the former is an expected conditional return, whereas, the latter is a difference in two expected conditional returns. Furthermore, the residual and difference in total returns metric approaches are no longer appropriately comparable in this context. This is true since the residual return metric involves only one realization of

$\tilde{\theta}$, while the difference in total returns metric involves two realizations of $\tilde{\theta}$.

Comparison of Metric Approaches in the Two Realization Case

With respect to the information hypothesis given by (3-2) and (3-3), comparing two different realizations θ_i and θ_j of $\tilde{\theta}$ involves a test of the equality of two means. Recall that the standard testing procedure is a joint test incorporating a priori contrasts. The simplest testing procedure available in this case is a Z test (assuming known variance) of the difference in two means. This test is given by

$$(3\text{-}20)\quad Z = \frac{(\hat{\gamma}_i - \hat{\gamma}_j) - 0}{[(\sigma^2(\tilde{e}_i) + \sigma^2(\tilde{e}_j) - 2\mathrm{Cov}(\tilde{e}_i,\tilde{e}_j))/n]^{\frac{1}{2}}}$$

The variance term in the denominator of the test is identical to the variance of the difference in returns metric (see (3-17) - (3-19)). Furthermore, the numerator is an estimate of this metric's expected value.

The residual return metric presented in (3-11) involves only one realization of $\tilde{\theta}$. However, a new metric could be constructed by taking the difference between two individual residual return metrics. This metric is given by

$$(3\text{-}21)\quad (\tilde{\varepsilon}/R_m,\theta_i) - (\tilde{\varepsilon}/R_m,\theta_j) = [(\tilde{R}/R_m,\theta_i) - \alpha - \beta R_m]$$

$$= - [(\tilde{R}/R_m,\theta_j) - \alpha - \beta R_m]$$

$$= (\gamma_i + \tilde{e}_i) - (\gamma_j + \tilde{e}_j)$$

$$= \gamma_i - \gamma_j + \tilde{e}_i - \tilde{e}_j.$$

The expected value and variance are, respectively,

$$(3\text{-}22)\quad E[(\tilde{\varepsilon}/R_m,\theta_i) - (\tilde{\varepsilon}/R_m,\theta_j)] = \gamma_i - \gamma_j + E(\tilde{e}_i) - E(\tilde{e}_j)$$

$$= \gamma_i - \gamma_j, \text{ and}$$

$$(3\text{-}23)\quad Var[(\tilde{\varepsilon}/R_m,\theta_i) - (\tilde{\varepsilon}/R_m,\theta_j)] = \sigma^2(\tilde{e}_i) + \sigma^2(\tilde{e}_j) - 2Cov(\tilde{e}_i,\tilde{e}_j).$$

Thus, the difference in the residual returns metric distribution parameters are the same as those of the difference in total returns metric. Moreover, this result is generalized for cases involving more than two realizations in Appendix A. Therefore, in these cases, the impact that each metric's variance has on the power of a test is identical.

Generalizing the results of Beaver's analysis to the two (or more) realization case implies one of two things. First, it might imply that θ_i can have information content, whereas, its compliment θ_j does not. If this holds, construction of the difference in residual returns metric would not be necessary in testing both realizations. This is true since the compliment's expected conditional return is assumed to be zero. Beaver [1980, p. 22], in fact, assumes this possibility in his analysis. In this regard, Gonedes [1974, p. 28] argues that the expected value of all conditional expected returns is zero in an efficient market. If this was not true, then $E(\tilde{R}) \neq \alpha + \beta E(\tilde{R}_m)$. For example, if θ_i and θ_j each occur fifty percent of the time, $E(\tilde{R}/\theta_i) = E(\tilde{R}) + C$, and $E(\tilde{R}/\theta_j) = E(\tilde{R})$, then $E(\tilde{R}) = (.5)E(\tilde{R}/\theta_i) + (.5)E(\tilde{R}/\theta_j) = (.5)[E(\tilde{R}) + C] + (.5)E(\tilde{R}) = E(\tilde{R}) + (.5)C$. This, of course, is impossible. The expected unconditional return cannot be equal to itself plus the additional term (.5)C.

The second possible implication is that the difference in total returns metric requires an unconditional return in its construction. Gonedes [1978], for example, uses unconditional returns in constructing the difference in total returns metric. If this requirement is necessary, then taking the difference of this difference would result in a variance which is not identical in form to that of the difference in two conditional residual (or total) returns (see (A-1) - (A-3)). However, employing *a priori* contrasts eliminates the need for this requirement.

The General Linear Model

Implemention of the standard testing procedure in cases involving more than two realizations of $\tilde{\theta}$ requires the use of analysis of variances (ANOVA) or in cases involving more than one dependent variable, multivariate analysis of variance (MANOVA). Both of these methods involve the formulation of a general linear model. More specifically, this is a model in which the dependent variable(s) is expressed as a linear function of the independent variable(s).

In market based research, the dependent variable(s) will be total return(s) or residual return(s). Accordingly, the model proposed later in this context will be referred to as a general linear return model (GLRM). Currently, the discipline of finance also expresses returns as a linear function using either the one-factor (market) model or the two-factor (zero-beta) model. The following discussion will explain: (1) the relationship between the GLRM and the two-factor model, and (2) the difference in total returns metric, incorporating both the two-factor model and GLRM.

Two-Factor (Zero-Beta) and General Linear Return Models

In general, the two-factor model is expressed as

$$(3\text{-}24) \quad \tilde{R} = \psi\tilde{R}_0 + \beta\tilde{R}_m + \tilde{u},$$

where $\tilde{R}_0$ is the return on a minimum variance zero-beta portfolio.

Imposition of the requirement that the market portfolio of positive variance securities be a minimum variance (and usually an efficient) portfolio implies that $\psi = (1 - \beta)$ (see Fama [1976, p. 301]). This, in turn, implies for any two securities (portfolios) z and q that if $\beta_z = \beta_q$, then $E(R_z) = E(R_q)$. The requirement is referred to as the equilibrium assumption and will be assumed throughout the following discussion.

The two-factor model can be expanded for conditional returns by including in the firm-specific component a fixed effect parameter. The model is given by

$$(3\text{-}25) \quad (\tilde{R}/\theta_i) = (1 - \beta)\tilde{R}_o + \beta\tilde{R}_m + \gamma_i + \tilde{\eta}_i \ .$$

This expansion is the same as introduced earlier regarding the one-factor model (see (3-9)).

The proposed general linear return model (GLRM) for conditional returns is given by

$$(3\text{-}26) \quad (\tilde{R}/\theta_i) = \mu + \gamma_i + (\tilde{v} + \tilde{\eta}_i)$$

$$= \mu + \gamma_i + \tilde{e}_i \ ,$$

where

μ = the grand mean,

γ_i = the ith level effect of θ_i, and

$\tilde{e}_i = (\tilde{v} + \tilde{\eta}_i)$ = the error term.

The components $\tilde{v}$ and $\tilde{\eta}_i$ are independent and each have an expected value of zero. This model is hypothesized for the one-factor (fixed effects) design case and is presented in detail in Chapter VI (see pages 80-81).

In this context, the term "factor(s)" refers to the fixed effect parameter(s) associated with the conditioning variable(s). For the two-factor (fixed effects) design case see Chapter VI pages 64-67.

The following derivation will demonstrate the equivalence of the two-factor model and the general linear return model for conditional returns.

$$
\begin{aligned}
(3\text{-}27)\quad (\tilde{R}/\theta_i) &= (1 - \beta)\tilde{R}_o + \beta\tilde{R}_m + \gamma_i + \tilde{\eta}_i \\
&= [(1 - \beta)\tilde{R}_o + \beta\tilde{R}_m] + \gamma_i + \tilde{\eta}_i \\
&= [(1 - \beta)E(\tilde{R}_o) + \beta E(\tilde{R}_m) + \tilde{v}] + \gamma_i + \tilde{\eta}_i \\
&= (\mu + \tilde{v}) + \gamma_i + \tilde{\eta}_i \\
&= \mu + \gamma_i + (\tilde{v} + \tilde{\eta}_i) \\
&= \mu + \gamma_i + \tilde{e}_i \ .
\end{aligned}
$$

In discussing the two models, their respective components will be dichotomized into economy-wide and firm-specific effects. The GLRM component $(\mu + \tilde{v})$ is a random variable with expected value μ. The two-factor model component $[(1 - \beta)\tilde{R}_o + \beta\tilde{R}_m]$ is a random variable with expected value $(1 - \beta)E(\tilde{R}_o) + \beta E(\tilde{R}_m)$. Both of these components are assumed to reflect economy-wide events, where μ equals $(1 - \beta)E(\tilde{R}_o) + \beta E(\tilde{R}_m)$. The other component in each model is identical, i.e., $\gamma_i + \tilde{\eta}_i$. This component has as its expected value the term γ_i and is assumed to reflect firm-specific events.

Given this equivalence, either model can be used to construct a difference in total returns metric.

$$(3\text{-}28)\quad d_{i,j} = (\tilde{R}/\theta_i) - (\tilde{R}/\theta_j)$$

$$= [(1 - \beta)\tilde{R}_o + \beta\tilde{R}_m + \gamma_i + \tilde{\eta}_i]$$

$$- [(1 - \beta)\tilde{R}_o + \beta\tilde{R}_m + \gamma_j + \tilde{\eta}_j]$$

$$= [((1 - \beta)E(\tilde{R}_o) + \beta E(\tilde{R}_m) + \tilde{v}) + \gamma_i + \tilde{\eta}_i]$$

$$- [((1 - \beta)E(\tilde{R}_o) + \beta E(\tilde{R}_m) + \tilde{v}) + \gamma_j + \tilde{\eta}_j]$$

$$= [(\mu + \tilde{v}) + \gamma_i + \tilde{\eta}_i]$$

$$- [(\mu + \tilde{v}) + \gamma_j + \tilde{\eta}_j]$$

$$= [\mu + \gamma_i + (\tilde{v} + \tilde{\eta}_i)] - [\mu + \gamma_j + (\tilde{v} + \tilde{\eta}_j)]$$

$$= [\mu + \gamma_i + \tilde{e}_i] - [\mu + \gamma_j + \tilde{e}_j]$$

$$= (\gamma_i + \tilde{e}_i) - (\gamma_j + \tilde{e}_j)$$

$$= \gamma_i - \gamma_j + \tilde{\eta}_i - \tilde{\eta}_j \; .$$

The expected value is the same as when the one-factor (market) model was employed. Furthermore, the variance has the same form, however, it will be smaller assuming the second factor $\tilde{R}_o$ explains some of the total variation in $\tilde{R}$.

Empirical Considerations

The discussion thus far has been in a conceptual setting. In more realistic environments, it is impossible using only the *ex post* return of an asset for a single period t to empirically estimate more than one value of γ. Even for one value, it would be impossible to estimate and statistically test for significance. When obtaining more observations by using an asset's *ex post* returns from various periods, though, concern must be given to possible changes in parameter values over time.

Alternatively, additional observations could be obtained by employing different asset returns for a given period. Using either alternative, the effect of θ is assumed to be homogeneous over time and/or among firms.

In the construction of "treatment" groups (portfolios), a researcher must control confounding variables. A confounding variable may be described as any variable which offers an alternative explanation regarding differences in the dependent variable(s) other than the "treatment". Total returns can differ among assets regardless of "treatment" effects since there may exist structural differences in their economy-wide components. This is attributable to differences in systematic risk measured by beta.

The two methods control this component differently. Residual return metric may employ properties of either the market model or the zero-beta model which would eliminate from the observed total return this component. Employing the market model for asset z results in

$$(3\text{-}29) \quad \hat{e}_z = R_z - \hat{\alpha}_z - \hat{\beta}_z R_m.$$

Portfolios of the estimated residuals can then be constructed.

With respect to the difference in total returns metric, portfolios are constructed so that the estimated parameters of the economy-wide components of each portfolio are equal. Under either model, imposition of the equilibrium assumption requires estimation of just one economy-wide parameter, i.e., beta. Hence, for two portfolios p and q their respective economy-wide components excluding estimation error would be equal if $\hat{\beta}_p = \hat{\beta}_q$.

Concluding Remarks

Both the residual return and difference in total return methods eliminate the "undesired" variability attributable to $\tilde{R}_m$ contained in the total return metric. However, interdependence among residuals might exist. If interdependence is detected, then statistical tests which assume independence are inappropriate.

Comparison of the two metrics employing a standard testing procedure is made in a conceptual setting. In cases involving two realizations of an "information" variable, it is shown that their econometric properties are identical. To provide the framework for cases involving more than two realizations, the general linear model from extant statistical theory is shown to be equivalent to the two-factor model. Although the same results can be reached without its use, this model is employed (see Appendix A) in the general case to demonstrate metric equivalence. This demonstration involves reparameterization of the model. This, in turn, results in *a priori* contrasts which are differences in total returns.

FOOTNOTES TO CHAPTER III

[1]An expected return represents only one parameter of the distribution. For an explanation of the general case see page 8.

[2]A contrast is defined as a weighted average of two or more population parameters such that the weights (coefficients) sum to zero.

CHAPTER IV

LITERATURE REVIEW OF REPLACEMENT (CURRENT) COST ACCOUNTING

Current Cost Concepts

Hicks [1946, p. 176] offers the following concept of income:

> . . .a person's income is what he can consume during the week and still expect to be as well off at the end of the week as he was at the beginning.

However, to operationalize this concept, one has to decide how wealth ("well-offness") is measured. Current cost advocates propose to define wealth as the current cost market value of assets. Within the Hicksian framework, a firm's expected current cost income is the amount of dividend a firm could distribute at the end of the period without impairing the current cost market value of its assets.

One of the major purported advantages to the current cost method of valuation is that it allows for dichotomization of the total income. Edwards and Bell refer to the two resultant components as current operating profit and realizable cost savings (RCS). Recall that current operating profit is defined as the difference between revenue and current cost of assets used to create that revenue. Realizable cost savings are defined as the difference between the current cost of assets at the end of a period or at time of sale and their current cost at the beginning of the period or at time or purchase if the assets are acquired in that interval. Purportedly, they measure changes in value attributable to firm operating and holding activities, respectively.[1] Specifically, current operating profit recognizes changes in value due to operating activities at time of sale, whereas, realizable cost savings recognizes changes in value due to holding activities when they occur. Edwards and Bell [1961, p. 73] explain the importance of distinguishing between the two different activities, stating:

> These two kinds of gains are often the result of quite different sets of decisions. The business firm usually has considerable freedom in deciding what quantity of assets to hold over time at any or all stages of the production process and what quantity of assets to commit to the production process itself. The opportunity to make profit through holding activities, that is, by holding assets while their prices rise, is probably not such an important alternative for most business firms as is the opportunity to make profits through operating activities, that is, by using asset services and other inputs in the production and sale of a product or service. The difference between the forces motivating the business firm to make profit by one means rather than by another and the difference between the events on which the two methods of making profit depend require that the two kinds of gain be carefully separated if the two types of decision involved are to be meaningfully evaluated.

Historical cost income (accounting profit) based solely on historical cost data cannot differentiate between these two activities. This is true since changes in value attributable to both activities are recognized at only one point in time, i.e., at time of sale. Therefore, any change in value through holding activities is not recognized when earned. However, by incorporating the current cost of those assets used in creating revenue, one could disaggregate accounting profit into current operating profit and realized cost savings. Edwards and Bell [1961, pp. 117-118] referring to this dichotomized accounting profit as realized profit state:

> A logical first step toward improving the accounting concept of profit is the reclassification of gains realized through use as cost savings rather than as operating profit. . .Such a measurement would have the advantage of drawing a sharp distinction in the records between current operating profit and realized cost savings. Management could better appraise its operating decisions because the results of current operations would no longer be confused with holding activities. National income statisticians would be able to accumulate aggregate profit figures for the economy with less difficulty and more accuracy. Similar benefits would accrue to financial analysts, creditors, and the public.

Object of Prediction

It has been argued that financial reports should provide information useful in predicting future values of relevant variables to decision makers. Evaluation of this reporting function is commonly referred to as the predictive ability criterion (Beaver, Kenelly, and Voss [1968]). Implementation problems arise, however, when one attempts to discover relevant variables or equivalently the real object of prediction since they may vary among users. Present knowledge of users' decision models is limited, therefore, theorists have attempted to isolate certain variables that would be of interest to a large user group. For example, one often suggested variable of interest to investors is future income.

Income, by definition, is an artifact and as such has no necessary external relevance. If, however, an income concept represents something of interest to users, then prediction of its own future value would provide through surrogation a future value of the real object of prediction. In this regard Revsine [1971] states:

> . . .the crucial issue in predictive ability is not the relative ability of an income concept to predict itself, but rather the ability of a concept to predict whatever object should be of concern to users.

Some theorists have viewed current cost income as a surrogate for economic income or equivalently distributable operating flow. Since the determinates of economic income are future cash flows (explained in more detail below), then distributable operating flow is the amount of cash that a firm can distribute, within a period, without impairing the value of its assets. Normative valuation models imply that investors desire information about their future cash flows. Therefore, income concepts that enhance predictive ability of future distributable operating flows should be beneficial.

The Theoretical Ability of Current Cost Accounting to Predict Future Distributable Operating Flow

In this section, it will be demonstrated in a theoretical setting that current operating profit is equal to distributable operating flow. In addition, two approaches for predicting future values of current operating profit and therefore distributable operating flow will be set forth. Both the interrelation and relative merits of each approach will be explored.

The subscript notation i/j will be employed in the following discussion. Thus, the symbol $V_{i/j}$ represents the value at time i of the discounted future net cash flows expected to be generated from a firm's assets measured as of time j. More formally,

$$(4\text{-}1) \qquad V_{i/j} = \frac{\sum_{k=i}^{n} R_{(k+1)/j}}{(1+r)^{k+1-i}} ,$$

where $R_{(k+1)/j}$ represents the expected (or actual net cash flow) in the (k+1)th period measured as of time j, r equals the market rate of interest and n represents the terminal date of the planning horizon. Edwards and Bell refer to this value as subjective value. Economic income is the difference between the subjective value of a firm's assets at the beginning and end of a period. At the beginning of a period, the ex ante measure is referred to as expected economic income (EEI). It is the income concept which is considered equivalent to distributable operating flow (DOF). Let 0 depict the beginning of a period and 1 the end of a period. Then, in symbols,

$$(4\text{-}2) \qquad EEI = V_{1/0} - V_{0/0} .$$

Eqivalently,

$$(4\text{-}3) \qquad EEI = V_{1/0} - V_{0/0}$$

$$= \frac{\sum_{k=0}^{n} R_{(k+1)/0}}{(1+r)^k} - \frac{\sum_{k=0}^{n} R_{(k+1)/0}}{(1+r)^{k+1}}$$

$$= \frac{(1+r)\sum_{k=0}^{n} R_{(k+1)/0}}{(1+r)^{k+1}} - \frac{\sum_{k=0}^{n} R_{(k+1)/0}}{(1+r)^{k+1}}$$

$$= (1+r)V_{0/0} - V_{0/0}$$

$$= rV_{0/0} + V_{0/0} - V_{0/0}$$

$$= rV_{0/0} \; .$$

At the end of the period, the ex post measure is reffered to as past (actual) economic income (PEI).

(4-4) $\quad PEI = V_{1/1} - V_{0/0} \; .$

Past economic income can be dichotomized into expected and unexpected economic income.

(4-5) $\quad PEI = V_{1/1} - V_{0/0}$

$$= V_{1/1} - V_{0/0} + V_{1/0} - V_{1/0}$$

$$= V_{1/1} - V_{0/0} + (1+r)V_{0/0} - V_{1/0}$$

$$= V_{1/1} - V_{0/0} + V_{0/0} + rV_{0/0} - V_{1/0}$$

$$= rV_{0/0} - (V_{1/1} - V_{1/0})$$

$$= EEI + UEI.$$

$$= DOF + UEI.$$

Assuming a perfectly competitive economy (Leftwich [1966, pp. 22-23]), in which all firms have homogeneous expectations implies that the price of every asset at time i is equal to its subjective value; i.e.,

$$(4\text{-}6)\quad P_{i/j} = V_{i/j}\ .$$

Furthermore, by substitution both expected current cost income (ECCI) and past current cost income (PCCI) equal their economic income counterparts[2]. In symbols,

$$(4\text{-}7)\quad ECCI = (R_{1/0} + P_{1/0}) - P_{0/0}$$

and

$$(4\text{-}8)\quad PCCI = (R_{1/1} + P_{1/1}) - P_{0/0}\ .$$

Assuming $R_{1/0}$ is realized (i.e., $R_{1/0} = R_{1/1}$) and employing the economic depreciation model, then expected and unexpected economic income can be interpreted as current operating profit and realizable cost savings. Rearranging (4-8), results in

$$\begin{aligned}(4\text{-}9)\quad PCCI &= (R_{1/1} + P_{1/1}) - P_{0/0} \\ &= (R_{1/1} + P_{1/1}) - P_{0/0} + P_{1/0} - P_{1/0} \\ &= (R_{1/1} - [P_{0/0} - P_{1/0}]) + P_{1/1} - P_{1/0} \\ &= COP + RCS \\ &= EEI + UEI\ ,\end{aligned}$$

where $(P_{0/0} - P_{1/0}) = (P_{0/0} - [(1+r)P_{0/0} - R_{1/0}])$ is economic depreciation.[3] The theoretical impact that this correspondence has on predicting future distributable operating flow will be explored next.

At the beginning of any period the realizable cost savings are expected to be zero. Therefore, expected current operating profit is equal to the total value of the assets times the interest rate and thus distributable operating flow. As Revsine [1973, p. 100] explains:

> To estimate future distributable operating flow, the following approach would be used. Since replacement cost income is equal to economic income in a perfectly competitive environment, the equity value shown on a replacement cost balance sheet would be equal to the net present value of the firm. Multiplying this net present value by the market rate of return on assets would provide an estimate of the succeeding year's distributable operating flow.

This prediction could also apply to periods beyond this year if it is assumed that the subjective value of the assets is maintained. Maintenance would be expected if all of the distributable operating flow is assumed to be distributed as a dividend. If, however, at the end of the period there exists a positive (negative) amount of realizable costs savings, then future period estimates of current operating profit would be revised upward (downward) at this time. Revsine refers to this as the lead indicator approach.

The other approach which is germane to this study is to extrapolate current operating profit for the period. Under both approaches, one is predicting future current operating profit. However, the two estimating procedures could result in different values. Within the framework of perfect competition, differences between approaches would only occur in those cases where the previous period's realizable costs savings was non-zero. To clarify, the lead indicator approach is designed to reflect changes in future cash flows as much as one period earlier than the extrapolation approach. Recall that these changes are initially reflected in the realizable cost savings component of the total current cost income. Therefore, in this framework the lead indicator approach is structurally superior.

This superiority is mitigated if price changes giving rise to realizable cost savings occur during the period (see footnote 3). Consequently, past current operating profit would deviate from expected current operating profit in the same direction as the price changes. Subsequent extrapolation of this period's past current operating profit reduces the difference between approaches. Thus, even in the advent of price changes, the interrelationship between approaches is apparent. That is, both approaches rely on the assumption of a positive covariance between asset prices and future cash flows for all firms.

Relaxation of the rigorous confines established by assuming perfect competition invokes additional considerations. Correspondence between economic income and current cost income is no longer perfect. Thus, current cost income only approximates economic income. This approximate relationship also holds for the respective subcomponents of each income concept. However, the predictive power of current cost income would not be seriously impaired if there still exists a positive covariance between changes in prices and changes in future cash flows.

In the long run for the economy as whole, this relationship should hold. However, there is no *a priori* reason to believe that this covariance will hold for all firms over each short run period. As a consequence, erroneous predictions could result. Given soundness of the theory, overall impact of departures from a perfectly competitive economy is, of course, an empirical question. Both frequency and magnitude of erroneous predictions should be explored under each approach. Unfortunately, in this regard no empirical research has been instigated to date.

Empirical Research

Studies by Hayes [1978], Gheyara and Boatsman [1980], Beaver, Christie, and Griffin [1980], and Ro [1980] have investigated the impact of ASR 190 replacement cost disclosures on security returns. In all four studies, no statistical significant association between security returns and ASR 190 disclosures was found.

Each of these studies used historical cost and/or Value Line estimates as proxies for the market's expectation of replacement cost data. A prominent feature of this research design which distinguishes it from previous studies is that actual replacement cost data are used to formulate an expectation model. Specifically, a firm's 1976 replacement cost data are employed in constructing that year's current operating profit which in turn forms the expectation for 1977. Deviations from each firm's actual 1977 current operating profit then form realizations of that conditioning variable.

The procedure employed in constructing information portfolios (i.e., partitioning firms) differs from the method used by Beaver et al.. Under their approach, the number of firms included in each information portfolio could vary. In fact, construction could result with information portfolios containing no firms. If the number of firms in each information portfolio is approximately equal then the conditioning variables should be considered crossed. Investigation into the relationship between conditioning variables was not reported by Beaver et al.. If, in fact, they were crossed, then interaction effects should have been tested or explicitly assumed to be zero. In this study, the relationship between conditioning variables is investigated to determine if they are crossed. See Chapter VI for a thorough discussion of this issue.

FOOTNOTES TO CHAPTER IV

[1]Drake and Dopuch [1965] criticize the ability of COP and RCS to reflect only operating and holding activities, respectively. They show that when a firm engages in speculative holding activities interdependencies between the two activities emerge. Revsine [1973, pp. 162-168] recognizes the validity of their arguments in cases involving speculative activities and therefore the resultant imperfection of this dichotomization. However, he defends the approaches for non-speculating firms.

[2]The argument that follows was originally presented by Revsine [1973]. His development and notation differ somewhat from the presentation here.

[3]If equality of $R_{1/0}$ and $R_{1/1}$ is dropped, then the difference $R_{1/1} - R_{1/0}$ can be viewed as unexpected current operating profit (UCOP). Therefore, UEI can be decomposed into UCOP and RCS or PEI = ECOP + UCOP + RCS. In the development presented it was assumed that price changes occur at the end of period. Therefore, deviations from ECOP would be considered random. However, (as discussed later) price changes could occur throughout the period. According to theory, the events giving rise to the price change would also create non-random deviations from ECOP in the direction of the price changes. The earlier they occur in the period, the greater the ultimate deviation.

CHAPTER V

DATA AND PORTFOLIO CONSTRUCTION

Firm Selection

Four criteria will be used to select firms for inclusion in the information sample portfolios: (1) current cost data were disclosed for both the years 1976 and 1977 on Reporting Forms 10-K; (2) at least seventeen years of the firm's earning data prior to and including 1977 are available on Standard and Poor's Compustat 1959-1978 tape; (3) the firm's consecutive daily price data are available on tape constructed by the Center for Research in Security Prices (CRSP) at the University of Chicago for each of the trading days corresponding to five hundred and fifty working days subsequent to and including March 31, 1978;[1] (4) the firm's fiscal year ends during or after April of each calendar year for which data are used.

Selection of firms to be included in the information sample will proceed as follows. Three digit numbers will be assigned to a list of six hundred and ninety-three firms required by ASR 190 to disclose current cost data. Employing a random number table, a firm will be randomly selected from a list and checked against the criteria mentioned above. If the firm meets the criteria, it will be included in the sample. Otherwise, it will be excluded. This procedure will be repeated until the sample contains one hundred and eight firms. This number of firms will be sufficient for constructing portfolios which provide reliable estimates of the risk parameters (betas). This issue will be discussed in detail later. See Appendix B for an industrial listing of firms actually selected.

External Validity

In a strict sense, one can generalize the results of this study only to the population of firms which meet all four criteria. Criterion (2) would tend to bias the results toward large and successful firms. However, one should expect a large overlap between sets of firms meeting both criterion (2) and criterion (1). This is true since ASR 190 requires that only large registraints disclose replacement cost data.[2] Furthermore, it is this latter set of firms which is of primary interest since they are the firms presently disclosing current cost data. The decision to generalize the results to a larger population including firms not presently disclosing current cost data is left to the reader.

Derivation of Income Forecast Errors

Firm accounting data obtained from 10-K reports and the Compustat tape were used to derive the historical cost income (HCI) and current operating profit (COP) forecast errors. Recall that values of these two forecast errors represent different realizations of the respective conditioning variables $\tilde{\theta}_1$ and $\tilde{\theta}_2$. Compustat variable 18, Income before Extraordinary Items and Discontinued Operations, was used to calculate each firm's HCI forecast error (HCIFE). This variable can be viewed as historical operating[3] profit and will be referred to hereafter as HCI. Using the martingale model (see (2-2)) as the investors' expectation model, derivation of the HCIFE was accomplished through two steps. First, the drift factor for firm i was calculated by using the following formula.

$$(5\text{-}1) \qquad \delta_i = \frac{HCI_{i,1976} - HCI_{i,[1976-(n-1)]}}{(n-1)} ,$$

where n is the number of HCI observations and, therefore, 1976 - (n-1) is the first observation in the sequence.[4] The second step, derivation of firm i's 1977 HCIFE was calculated using the formula given below.

$$(5\text{-}2) \quad HCIFE_{i,1977} = HCI_{i,1977} - (HCI_{i,1976} + \delta_i).$$

In words, the expected HCI for 1977 is given by the actual HCI for 1976 plus the drift factor δ, i.e., $E(HCI_{1977}/HCI_{1976},\delta) = HCI_{1976} + \delta$. Therefore, the HCI forecast error for 1977 is the difference between the actual HCI and its expected value.

From the 10-K reports of 1976 and 1977, each firm's reported replacement cost depreciation and cost of goods sold expense figures and their corresponding historical cost counterparts were obtained. Recall that these two expense categories are the only types required by the Security and Exchange Commission to be restated on a replacement cost basis. Although the other expenses were not reported on a replacement cost basis, these two are (for most firms) the primary components of the total reported expense. Furthermore, differences between the two valuation methods with respect to many of the other expense categories would be small or zero. This is true since these expensed assets are utilized in the creation of revenue close to or concurrent with their historical date of acquisition. For example, administrative salaries are assumed to be acquired and utilized concurrently and therefore the expensed amount would be the same under either method. Therefore, derivation of the COP employing only this data should result in a reasonable approximation of current operating profit. This derivation is the result of adding historical cost depreciation and cost of goods sold expenses to the HCI and then deducting from this subtotal the replacement cost depreciation and cost of goods sold expenses. With completion of this process, derivation of the COP forecast error (COPFE) is discussed next.

Each firm's 1977 COPFE was calculated by employing the following formula.

$$(5\text{-}3)\qquad COPFE_{i,1977} = COP_{i,1977} - COP_{i,1976} \;.$$

The drift factor was omitted because only one pre-1977 COP value existed. It is, therefore, assumed to be zero.

Finally, to obtain meaningful comparisons between firms, both forecast errors were standardized. This was accomplished by dividing each error by the estimated standard deviation of the HCI forecast error. The estimated standard deviation for each firm i was calculated using the following formula.

$$(5\text{-}4)\qquad S(HCIFE) = \left(\sum_{j=1}^{n-1}[HCIFE_{i,j} - \overline{HCIFE}_{i,j}]^2/(n-2)\right)^{\frac{1}{2}},$$

where

$$\overline{HCIFE} = \left(\sum_{j=1}^{n-1} HCIFE_{i,j}\right)/(n-1).$$

Weekly Returns

The dependent variables in this study are weekly returns. Simple daily total returns of the form given by (3-1) are obtained from the CRSP tapes. Therefore, each firm's five hundred and fifty consecutive daily returns (excluding week-ends and holidays) will be converted into simple weekly returns consisting of five working days each. That conversion will be done as follows:

$$(5\text{-}5)\qquad R_{i,t} = (1 + r_{i,t,1})(1 + r_{i,t,2}) \;.\;.\;.\; (1 + r_{i,t,5}) - 1,$$

where

$R_{i,t}$ = the ith firm's weekly return for week t, and

$r_{i,t,j}$ = the ith firm's daily returns for days j = 1,2,...,5 in week t.

Through this process the five hundred and fifty daily return period is converted into a one hundred and ten weekly return period. The first sixty weeks form the beta estimation period and the remaining fifty weeks provide the test period. From a statistical point of view, each week in the test period is treated as a observation. Therefore, the sample contains fifty observations. These two subperiods are depicted in figure 5-1 and will be discussed in more detail below.

Portfolio Construction

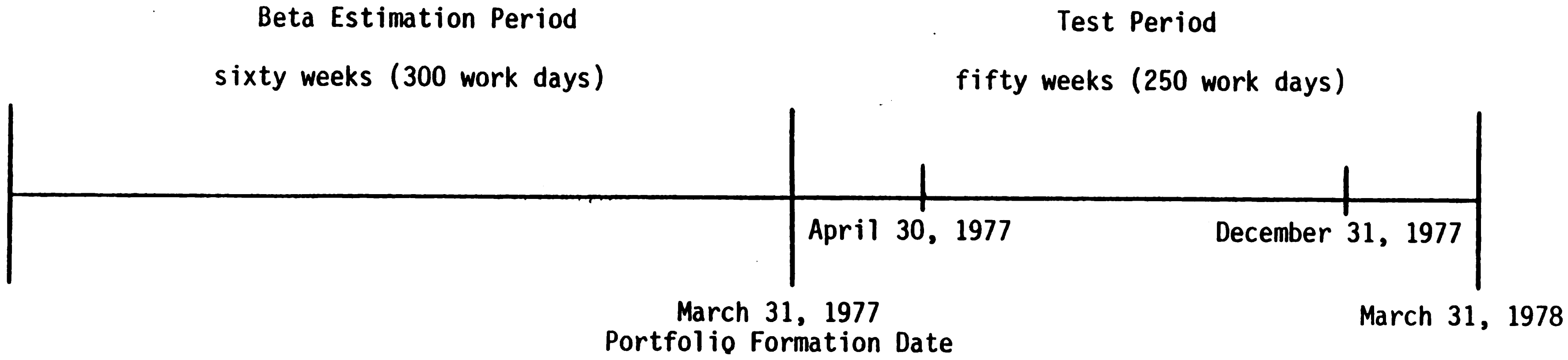
All procedures to be employed in constructing portfolios are discussed by Gonedes [1975 and 1978]. Regarding the use of portfolio formation dates he states [1975, p. 233]:

> Using March of each fiscal year as portfolio formation month seems most appropriate for firms with December 31 fiscal years because, on average, such firms announce their annual accounting numbers in March. The above procedures are, however, also applicable to firms with fiscal years ending after March 31, but before December 31, if the results are appropriately interpreted. The appropriate interpretation is that the estimated conditional distribution functions are conditional upon: (a) holding portfolios fixed for a 12-month period, (b) announcements of specified realizations of $\tilde{\theta}_{it}$ -- one for each i -- sometime within this 12-month period, and (c) forming portfolios during or at the end of a fiscal year and before that year's annual accounting numbers are announced. Including non-December 31 firms in our sample seems to increase the generality of our results. But the increase hardly seems dramatic since about 76 percent of the sample firms have December 31 fiscal years.

There will only be one formation date, March 31, 1977, used in constructing portfolios. Given criterion (4) there will be at least one and at most nine months between the formation date and the last month of each firm's fiscal year (see figure 5-1). Reported accounting numbers, however, might not become available to the market until three months after the firm's fiscal year end.[5] Therefore, information portfolios

Figure 5-1

Beta Estimation and Test Periods



will be formed conditioned on different HCI and COP forecast error realizations, which are assumed to become available any time within the twelve month period subsequent to the formation date. This twelve month period is equivalent to the fifty week test period described above.

There has been concern over the imprecise knowledge of the event date in market based research. Watts and Zimmerman [1980, p. 104] summarize this problem in stating:

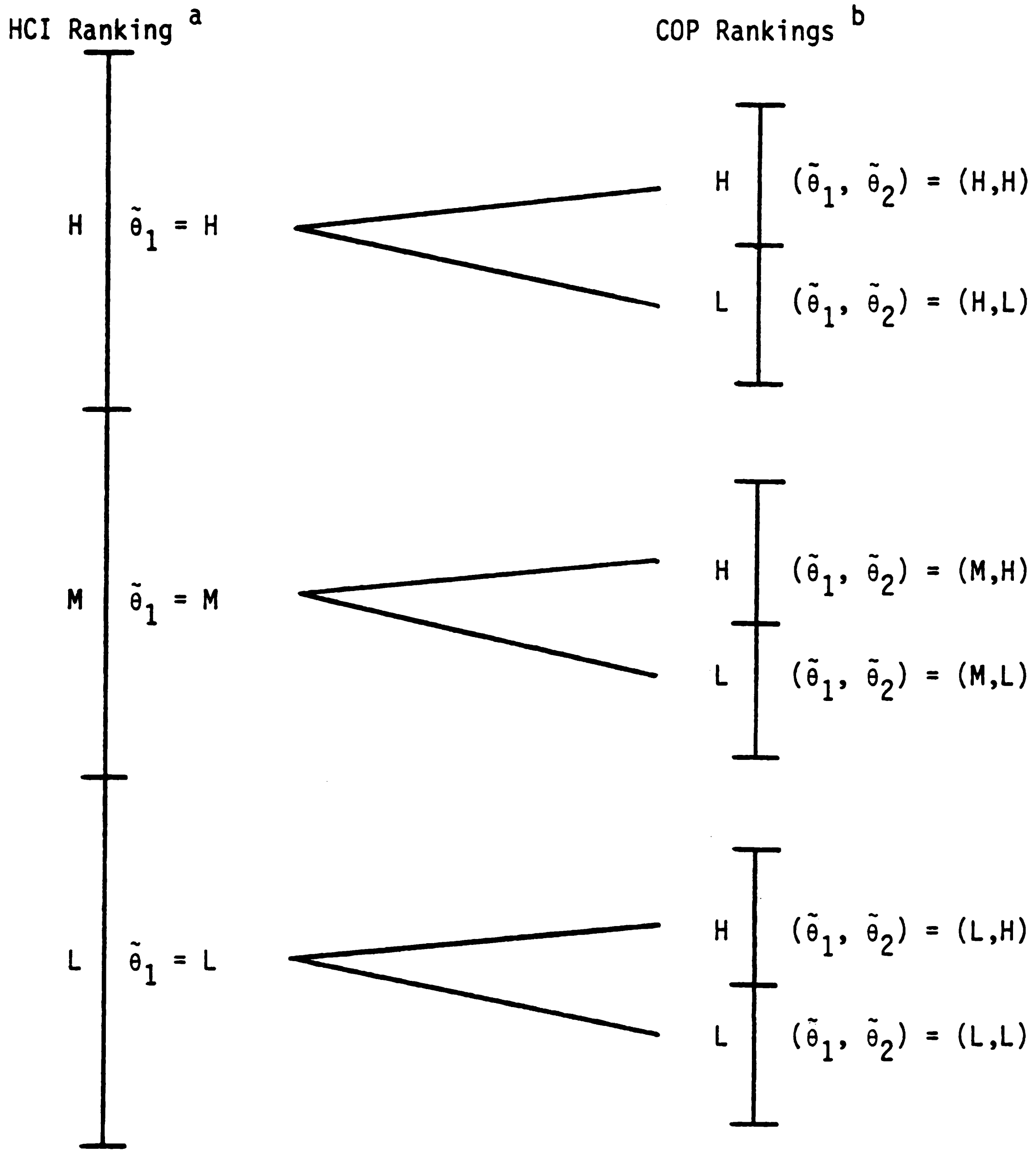
> Does the market revise expectations on the day the information is realised or prior to and through the release date due to alternative sources of information?. . .This problem forces the researcher to make a trade-off. The fewer the number of days being examined, the greater the signal to noise ratio and the more powerful the test. But at the same time, the fewer the number of days, the greater the likelihood that some or all of the total price change has already occurred due to alternative sources of information.

Since all one hundred and eight firms have December 31 fiscal years, additional tests will be made for each of the following three subperiods: (1) twelve weeks before and after December 31; (2) twelve weeks before December 31; and (3) twelve weeks after December 31.

In constructing information portfolios, firms in the information sample will be ranked according to their standardized HCI forecast errors and then divided into three non-overlapping groups: high (H), middle (M), and low (L). These three designating group values will represent the possible realizations of $\tilde{\theta}_1$. Then, firms within each of these groups will be ranked according to their standardized COP forecast errors and divided into two groups: high (H) and low (L). These two designating group values will represent the realizations of $\tilde{\theta}_2$. The result of this procedure will be six (3 x 2) different information groups, each containing eighteen firms. Figure 5-2 pictorially reviews the construction process and summarizes the six forecast error realizations of $\tilde{\theta} = (\tilde{\theta}_1, \tilde{\theta}_2)$. By construction these realizations will form the various conditioning

Figure 5-2

Review of Construction Process and
Summary of Forecast Error Realizations



[a] One group of one hundred and eight firms ranked according to their HCI forecast errors

[b] Three groups of thirty-six firms each ranked according to their COP forecast errors

values of the information portfolios.

To proceed further with the construction of portfolios, the motivation for such construction must be explained.

Within the experimental design context, one attempts to construct samples (portfolios) so that pre-experimental sample equivalence exists; i.e., one attempts to hold all things other than the "treatment(s)" equal. Recall that according to the version of the CAPM given by (2-1) the only parameter which differentiates between portfolio equilibrium expected returns at time t, the formation date, is beta. All information portfolios would be constructed with equal betas. Therefore, the only difference between each information portfolio would be the "treatments". These "treatments" are by construction the different realizations of $\tilde{\theta}$ which become available to the market after the formation date.

Portfolios will be constructed from the six groups as follows: (1) upon aggregation of daily returns, into weekly returns, beta for each form will be estimated by applying sixty weeks of return data from the beta estimation period to the market model; (2) for each group, firms will be ranked according to their estimated betas and then divided at the median into equally weighted high and low risk portfolios; (3) for each group, the high and low risk portfolios will be combined with weights which add to one so that the resulting portfolio has an estimated beta equal to one. More formally,

(5-6) $\quad 1 = x\hat{\beta}_H + (1 - x)\hat{\beta}_L$,

where

$\hat{\beta}_H$ = the estimated beta of an equally weighted high risk portfolio,

$\hat{\beta}_L$ = the estimated beta of an equally weighted low risk portfolio, and

$x, (1-x)$ = the weights.

Results of Portfolio Construction

The actual estimated betas used in constructing each set of equally weighted high and low risk portfolios are presented in Table 5-1. For each set, the table also shows betas for each high and low risk portfolio along with their respective weights. As mentioned above, these weights are used to combine each of the portfolio sets to form the six equal beta information portfolios. Recall, in this study equality is attained by setting beta equal to one.

Reviewing the results, there is only one case (M,H) that the prespecified value of unity did not fall within the range of values defined by the equally weighted high and low risk portfolios. In this case the low risk portfolio weight has a value less than zero. Negative weight implies that this portfolio is sold short. This construction process then determines how each portfolio return is established from the observed returns of securities comprising it.

The weekly returns for each information portfolio were then calculated in two steps. In step one, the weekly return for each high and low risk portfolio was calculated by

$$(5\text{-}7) \qquad R_{\hat{\beta}_{H(L)}} = \sum_{i=1}^{9} R_i/9.$$

Then in step two, the return for each information portfolio was calculated by

$$(5\text{-}8) \qquad R_I = xR_{\hat{\beta}_H} + (1 - x)R_{\hat{\beta}_L} .$$

Each resulting set of six weekly returns represent the observed measures of the design. At the portfolio formation date, their expected returns

Table 5-1

Security and Portfolio Betas

	Information Portfolios					
	(L,L)	(L,H)	(M,L)	(M,H)	(H,L)	(H,H)
	Individual Security Betas for the Equally Weighted High Risk Portfolios					
	1.667029	1.775445	2.649679	1.172304	1.752493	1.787479
	1.434967	1.562208	1.820371	1.134310	1.520941	1.500210
	1.242371	1.474098	1.347095	1.043278	1.211616	1.404480
	1.057531	1.274420	1.170336	1.006278	1.173266	1.217990
	1.045827	1.174276	1.146689	.947367	1.129478	1.135438
	.903220	1.161185	1.005060	.896346	1.048634	1.005791
	.899631	1.120045	.917951	.872150	1.029532	.955707
	.882591	1.036045	.884583	.828662	1.026163	.916336
	.870760	.859770	.853825	.797978	.740036	.913178
Total	10.003927	11.437492	11.795589	8.698664	10.632159	10.836609
Average	1.111547	1.270832	1.310621	.966518	1.181351	1.204068
High Risk Portfolio Weight (x)	.848927	.692525	.625532	1.083675	.791051	.781932
	Individual Security Betas for the Equally Weighted Low Risk Portfolios					
	.733547	.811465	.727968	.797423	.583013	.801533
	.653992	.692757	.667873	.797316	.398901	.593414
	.614145	.690822	.666884	.637696	.394231	.560295
	.540192	.661564	.661152	.597071	.323071	.514206
	.312438	.583049	.653871	.594562	.272701	.244482
	.266101	.355764	.319238	.496981	.251648	.229146
	.141359	.303181	.287887	.441027	.245837	.201222
	.121035	.210854	.265266	.424493	.188272	.144283
	(.024178)	(.799404)	.079953	.310813	.163219	(.874167)
Total	3.358631	3.510052	4.330092	5.097382	2.820893	2.414414
Average	.373181	.390005	.481121	.566376	.313432	.268268
Low Risk Portfolio Weight (1-x)	.151073	.307475	.374468	(.083675)	.208979	.218068

are assumed to be equal. Therefore, any significant differences over the fifty week test period would imply information content.

Internal Validity

Ideally, in the experimental setting one attempts to assure pre-experimental equivalence by randomly assigning subjects to treatments. Randomization, of course, is not possible in this study. In lieu of this, imposition of the equilibrium assumption, if $\beta_i = \beta_j$, then $E(\tilde{R}_i) = E(\tilde{R}_j)$ provides the rationale for obtaining pre-experimental equivalence. However, in attempting to set all portfolio betas equal, errors might arise. This is because true beta values are not available, and must be estimated from _ex post_ returns (Fama [1976, p. 344]. Departures from equality arising due to estimation errors could therefore affect the obtainment of pre-experimental equivalence. Unfortunately, the absence of this equivalence provides an alternative explanation for any systematic difference(s) (or lack thereof) discovered. For example, if in comparing two portfolios' returns, one portfolio had an actual beta greater than the other, then according to the CAPM their expected returns should differ regardless of any "treatment" effect.

The researcher should attempt to minimize this threat to internal validity by obtaining the most precise beta estimates possible. This problem of estimating beta with precision is one reason for grouping securities into portfolios. Fama and McBeth have shown the effecttiveness of the portfolio approach. Their test results revealed that $S(\sum_{i=1}^{n} e_i) = S(e_p)$ is one-third to one-seventh the magnitude of $\sum_{i=1}^{n} S(e_i)/n$, where S(e) is the estimated standard derivation of the error. Furthermore, this result implies that the standard error of a portfolio beta estimate $S(\hat{\beta}_p)$ is also one-third to one-seventh the magnitude of the standard error of an individual security beta estimation $S(\hat{\beta}_i)$ (see Fama [1976, pp. 351-356]).

FOOTNOTES TO CHAPTER V

[1]There was one exception. Kaiser Steel Corporation had incomplete data. Missing return data was obtained from the Standard and Poor's Daily Stock Price Record.

[2]ASR 190 excludes those firms whose total inventory and gross property, plant, and equipment are either less than one hundred million dollars or ten percent of the total asset value.

[3]Although one might take exception to the term operating, this figure can be considered as the historical counterpart to current operating profit as defined by Edwards and Bell [1961, pp. 111-121].

[4]Ball et al. [1976] presented evidence that the longer the period employed to compute δ, the lower the mean absolute forecast error.

[5]Ball and Brown [1968, pp. 166-167] found that seventy-five percent of the 1957 firms in their sample of December 31 year-end firms had made a preliminary year-end report by March 10 of the following year. The length of time between the year-end and the release of these reports gradually shortened for the years included in their sample so that by the final year, 1965, seventy-five percent of the firms released a preliminary report by February 21 of the following year. The entire annual report must be made available to the public by at least the ninetieth day after fiscal year-end, which is the last day for filing Form 10-K with the SEC (see Rappaport [1972, pp. 14.5-14.7]).

CHAPTER VI

HYPOTHESES AND EXPERIMENTAL DESIGN

Statement and Test of the Omnibus Hypothesis

Omitting the subscript t for convenience and using underlined notations to refer to vectors, let $\underline{\tilde{R}}_1$ and $\underline{\tilde{R}}_2$ denote two 6x1 vectors of returns for the information and control samples, respectively. By construction, the components of each vector are formed to have a beta equal to one. The estimate, then, of $E(\underline{\tilde{R}}_1)$ will differ from the estimate of $E(\underline{\tilde{R}}_2)$ only because each component of the former will be an estimated mean return conditioned on a realization (e.g., H,L) of the "information" vector $\underline{\tilde{\theta}}$. By following this construction, the properties of the two-parameter model will be exploited so that any difference in the estimates will be attributed to realizations of $\underline{\tilde{\theta}}$ rather than difference in the specific assets represented in $\underline{\tilde{R}}_1$ and $\underline{\tilde{R}}_2$. To emphasize this point notational changes will be made by substituting $E(\underline{\tilde{R}}/\underline{\theta})$ and $E(\underline{\tilde{R}})$ for $E(\underline{\tilde{R}}_1)$ and $E(\underline{\tilde{R}}_2)$, repectively.

Recall, the following two assumptions were made: (1) capital markets are efficient and (2) all joint conditional and unconditional security return distribution functions are multivariate normal. The second assumption regarding the nature of these distribution functions as disucssed in Chapter II is sufficient but not necessary for testing the hypotheses.

The omnibus null hypothesis is $E(\underline{\tilde{R}}/\underline{\theta}) = E(\underline{\tilde{R}})$. Setting $\underline{\mu}_d = E(\underline{\tilde{R}}/\underline{\theta}) - E(\underline{\tilde{R}})$ this hypothesis is equivalent to:

(6-1) H_o: $\underline{w}'[E(\underline{\tilde{R}}/\underline{\theta}) - E(\underline{\tilde{R}})] = \underline{w}'\underline{\mu}_d = \underline{\mu}_o = 0$ for all values of the 6x1 vector $\underline{w}$.

The multivariate hypothesis is stated in terms of mean vectors so that joint simultaneous tests will be performed on all realizations of the "information" variable(s). Each component of the difference vector $\underline{\mu}_d$ represents a proposition that the mean return difference between the information portfolio and a control portfolio is zero. The weight vector $\underline{w}$ generalizes the hypothesis to include all linear combinations of the six mean return differences. Acceptance of this hypothesis would imply that $\underline{\theta}$ reflects no information.

In the alternative hypothesis, there exists at least one realization, $\underline{\tilde{\theta}}$ of $\underline{\tilde{\theta}}$, so that the equality in (6-1) does not hold. The alternative hypothesis is given by

$$\text{(6-1')} \quad H_1: \quad \underline{w}'\underline{\mu}_d \neq \underline{\mu}_o = \underline{0} \text{ for some } \underline{w}.$$

Acceptance of this hypothesis would imply that $\underline{\tilde{\theta}}$ reflects information.

The following procedure is used in estimating the mean return difference parameter $\underline{\mu}_d$. The year consists of fifty five work day periods each of which is considered a week. Weekly returns of each portfolio are computed throughout the fifty week period subsequent to the March 31, 1977 portfolio formation date. Each control sample portfolio is arbitrarily paired with one information sample portfolio forming six pairs. For each week in the test period the difference between the weekly return of an information sample portfolio and its corresponding control sample portfolio is calculated. Each resulting set of fifty calculations corresponding to portfolio pairs is used to estimate each of the six components of the expected mean difference vector parameter $\underline{\mu}_d$.

The statistical test that is used in testing the omnibus null hypothesis is Hotelling's T^2. This test, a generalization of the univariate t test, is an appropriate test of the hypothesis given the above mentioned assumption that security returns are multivariate normal.[1] The T^2 statistic to be used in this test has the form

$$(6\text{-}2) \quad T^2 = \max t^2(\underline{w}) = [w'(\underline{\bar{d}} - \underline{\mu}_0)(\underline{\bar{d}} - \underline{\mu}_0)'\underline{w}N]/(w'Sw),$$

where $\underline{w}$ is previously defined in (6-1); $\underline{\bar{d}}$ is the estimate of the expected mean difference parameter $\underline{\mu}_d$; N is the sample size; and S is the sample covariance matrix of $(\underline{\tilde{R}}/\underline{\theta}) - \underline{\tilde{R}} = \underline{\bar{d}}$. The hypothesized value of $\underline{\mu}_0$ is the null vector, and may be dropped from the expression.

In constructing a single test statistic for the mean vector hypothesis, (6-2) employs a weight vector $\underline{w}$ which forms a linear combination with the components of the mean difference vector $\underline{\bar{d}}$. Although any set of values can be assigned to the weight vector $\underline{w}$, the T^2 statistic uses that set which maximizes the value of T^2.

The statistic $t^2(\underline{w})$ is unaffected by a change in scale of the components of $\underline{w}$. This property creates a problem of indeterminancy with respect to the set of values of $\underline{w}$ which maximizes T^2. This problem can be resolved by imposing the constraint $\underline{w}'S\underline{w} = 1$. The imposition of the constraint leads to an equivalent form of (6-2).

$$(6\text{-}3) \quad T^2 = N(\underline{\bar{d}} - \underline{\mu}_0)'S^{-1}(\underline{\bar{d}} - \underline{\mu}_0).$$

This invariance of $t^2(\underline{w})$ to scalar multiples of $\underline{w}$ also allows the set of values of $\underline{w}$ associated with any value of $t^2(\underline{w})$ to be normalized so that the set sums to unity. The normalized set of values of that $\underline{w}$ which maximizes $t^2(\underline{w})$ can be calculated by multiplying the vector $\underline{y} = S^{-1}(\underline{\bar{d}} - \underline{\mu}_0)$ by the scalar $1/\sum_{p=1}^{P} y_p$ The resulting normalized set of values form a legitimate set of portfolio weights.

When the null hypothesis is true, the T^2 statistic can be transformed to the F statistic:

$$(6\text{-}4) \qquad F = \frac{(N - P)}{P(N - 1)} T^2 .$$

This F distribution has P and N - P degrees of freedom where P equals the number of portfolio pairs, and N is the number of weekly observations. Departures of $\underline{\mu}_d$ from $\underline{\mu}_o$ increase the expected value of T^2, and therefore the value of the calculated F statistic. The decision rule for a given level of significance α will be to accept the null hypothesis if the calculated F statistic is less than the critical F value. Otherwise, reject the null hypothesis and infer that the income forecast errors have information content.

However, under the null hypothesis given by (6-1) each component of the vector of conditional expected returns, $E(\tilde{R}/\underline{\theta}_i)$, i = 1,...,6, is equal to the unconditional expected return, $E(\tilde{R})$. Therefore, an equivalent statement of this hypothesis is that all conditional expected returns are equal to each other:

$$(6\text{-}5) \qquad E(\tilde{R}/\underline{\theta}_i) - E(\tilde{R}/\underline{\theta}_j) = 0, \; i,j = 1,\ldots,6, \; i \neq j.$$

Viewing the hypothesis in this form lends itself more clearly than the hypothesis given by (6-1) to the experimental-design model approach to hypothesis formulation and testing. Furthermore, control portfolios are unnecessary and thus the distribution assumption regarding unconditional returns can be dropped.

Experimental-Design Approach

Multivariate Analysis of Variance (MANOVA)

Under this approach a general linear model is hypothesized and the parameters are estimated. Hypothesis testing will be introduced as an adjunct to this estimation procedure.[2] In addressing the model issue recall that the method to be used in constructing portfolios will yield six information portfolios "identical" except for the treatments, i.e., the six different combinations of the three realizations of $\tilde{\theta}_1$ and the two realizations of $\tilde{\theta}_2$. This can be viewed as a design with two factors over measures, where the measures are simple weekly returns on portfolios. The first factor $\tilde{\theta}_1$ has three levels: high (H), middle (M) and low (L). The second factor $\tilde{\theta}_2$ has two levels: high (H) and low (L). This design will be referred to as a 3x2 factorial design over measures (3x2 D/M). See Figure 6-1 for a pictorial representation.

The following linear model is hypothesized for this 3x2 D/M:

$$(\tilde{R}/\underline{\theta})_{ijt} = \mu + \gamma_i + \beta_j + (\gamma\beta)_{ij} + \tilde{e}_{ijt}, \ i = 1,2,3, \ j = 1,2, \quad t = 1,2,\ldots,50 \tag{6-6}$$

where

$(\tilde{R}/\underline{\theta})_{ijt}$ = the observed portfolio return in the (ij)th treatment for week t;

μ = the grand mean;

$\mu_{i.}$ = the mean for the ith treatment;

$\mu_{.j}$ = the mean for the jth treatment;

$\mu_{ij} = \mu + \gamma_i + \beta_j + (\gamma\beta)_{ij}$ = the mean for the (ij)th treatment;

Figure 6-1

Two-Factor Design

$\tilde{\theta}_1$ \ $\tilde{\theta}_2$	high (H)	low (L)	marginal means
high (H)	$\bar{y}_{11.}$	$\bar{y}_{12.}$	$\bar{y}_{1..}$
middle (M)	$\bar{y}_{21.}$	$\bar{y}_{22.}$	$\bar{y}_{2..}$
low (L)	$\bar{y}_{31.}$	$\bar{y}_{32.}$	$\bar{y}_{3..}$
marginal means	$\bar{y}_{.1.}$	$\bar{y}_{.2.}$	$\bar{y}_{...}$

Key: - denotes average

. is used to replace the t, i, or j and indicates that the t, i, and/or j have been "summed over".

$\bar{y}_{ij.}$ is the observed average portfolio return in the (ij)th treatment for the 50 week period.

$\bar{y}_{i..}$ is the observed average portfolio return in the ith treatment for the 50 week period.

$\bar{y}_{.j.}$ is the observed average portfolio return in the jth treatment for the 50 week period.

$\bar{y}_{...}$ is the observed average portfolio return for the 50 week period.

$\gamma_i = (\mu_{i.} - \mu)$ = the ith level HCI forecast error effect;

$\beta_j = (\mu_{.j} - \mu)$ = the jth level COP forecast error effect;

$(\gamma\beta)_{ij} = \mu_{ij} - (\mu + \gamma_i + \beta_j)$ = the (ij)th interaction effect;

$\tilde{e}_{ijt}$ = the error term.

Moreover, γ_i is the main effect of class i in γ,β_j is the main effect of class j in β, and $(\gamma\beta)_{i,j}$ is an effect specific to subclass i,j. This model is the two-factor version of the general linear return model given by (3-26).

In this model, the numbers one and zero are implied coefficients of the μ, γ_i, β_j and $(\gamma\beta)_{ij}$ terms. Thus, the first equation may be written as

$$(\tilde{R}/\underline{\theta})_{11t} = 1\mu + 1\gamma_1 + 0\gamma_2 + 0\gamma_3 + 1\beta_1 + 0\beta_2 + 1(\gamma\beta)_{11} + 0(\gamma\beta)_{12} + 0(\gamma\beta)_{21} + 0(\gamma\beta)_{22} + 0(\gamma\beta)_{31} + 0(\gamma\beta)_{32} + \tilde{e}_{11t}$$

This equation states that the return in week t of a portfolio in treatment 1, 1 is the sum of an effect μ general to all treatment combinations, plus an effect γ, due to treatment 1 of the first experimental factor, plus an effect β_1 due to treatment 1 of the second factor, plus an interaction effect $(\gamma\beta)_{11}$ due to the treatment combination of both factors, plus a random component $\tilde{e}_{11t}$. For clarity and ease of discussion, the model will be presented in matrix form before proceeding with estimation and hypothesis testing.

Let $\underline{\tilde{Y}}.$ denote the 6x1 vector of means $\tilde{\bar{y}}_{ij.}$ from a hypothetical random sample, then the matrix representation of the model in (6-6) is given by the expression

(6-7) $\underline{\tilde{Y}}. = A\underline{\xi} + \underline{\tilde{\varepsilon}}$, where

$$A = \begin{bmatrix} 1 & 1 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix},$$

$$\underline{\xi} = \begin{bmatrix} \mu \\ \gamma_1 \\ \gamma_2 \\ \gamma_3 \\ \beta_1 \\ \beta_2 \\ (\gamma\beta)_{11} \\ (\gamma\beta)_{12} \\ (\gamma\beta)_{21} \\ (\gamma\beta)_{22} \\ (\gamma\beta)_{31} \\ (\gamma\beta)_{32} \end{bmatrix},$$

and $\underline{\varepsilon}.$ denotes the 6x1 random error vector and is assumed to be distributed $N(\underline{0},\Sigma)$, where $\underline{0}$ is a 6x1 vector of zeros and Σ is the variance-covariance matrix. For convenience, the tildes on $\tilde{\underline{y}}.$ and $\tilde{\underline{\varepsilon}}.$ are dropped.

In the matrix representation of the model, rows of matrix A contain ones and zeros that were implied implicitly in (6-6). Since there are twelve unknown parameters and only six equations in the model, a unique solution does not exist (that is, the matrix A is singular and therefore, AA^{-1} does not exist). This problem can be overcome by reparameterizing the model so that the number of unknowns is reduced to six. The reparameterization process will yield a new set of parameters which are a linear combination of the old set. Furthermore, by selecting the appropriate reparameterization matrix, the new parameters will represent the *a priori* contrasts of interest to the researcher. Mechanics of this process are presented below.

Reparameterization is achieved by factoring the A matrix into the product of two matrices K and L.

(6-8) $A = KL.$

Matrix L is the row basis of A and matrix K is the column basis of A.

(6-9) $L = (K'K)^{-1}KA.$

(6-10) $K = AL'(LL')^{-1}.$

Substituting KL into the original model and premultiplying $\underline{\xi}$ by L results in a 6x1 vector $\underline{\phi}$. The components of $\underline{\phi}$ represent a new set of parameters which are a linear combination of the components of $\underline{\xi}$. The last five combinations form the *a priori* contrasts of interest. The new model is

$$
\begin{aligned}
(6\text{-}11)\quad \underline{Y}. &= KL\underline{\xi} + \underline{\varepsilon}. \\
&= K(L\underline{\xi}) + \underline{\varepsilon}. \\
&= K\underline{\phi} + \underline{\varepsilon}.
\end{aligned}
$$

In this study the parameterization matrix L is

$$\begin{bmatrix} 1 & 1/3 & 1/3 & 1/3 & 1/2 & 1/2 & 1/6 & 1/6 & 1/6 & 1/6 & 1/6 & 1/6 \\ 0 & 1 & 0 & -1 & 0 & 0 & 1/2 & 1/2 & 0 & 0 & -1/2 & -1/2 \\ 0 & 0 & 1 & -1 & 0 & 0 & 0 & 0 & 1/2 & 1/2 & -1/2 & -1/2 \\ 0 & 0 & 0 & 0 & 1 & -1 & 1/3 & -1/3 & 1/3 & -1/3 & 1/3 & -1/3 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 0 & -1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & -1 & 1 \end{bmatrix}.$$

Premultiplying $\underline{\xi}$ by L results in

$$\underline{\phi} = \begin{bmatrix} \mu + (\gamma_1 + \gamma_2 + \gamma_3)/3 + (\beta_1 + \beta_2)/2 + [(\gamma\beta)_{11} + \cdots + (\gamma\beta)_{32}]/6 \\ (\gamma_1 - \gamma_3) + [(\gamma\beta)_{11} + (\gamma\beta)_{12} - (\gamma\beta)_{31} - (\gamma\beta)_{32}]/2 \\ (\gamma_2 - \gamma_3) + [(\gamma\beta)_{21} + (\gamma\beta)_{22} - (\gamma\beta)_{31} - (\gamma\beta)_{32}]/2 \\ (\beta_1 - \beta_2) + [(\gamma\beta)_{11} - (\gamma\beta)_{12} + (\gamma\beta)_{21} - (\gamma\beta)_{22} + (\gamma\beta)_{31} - (\gamma\beta)_{32}]/3 \\ (\gamma\beta)_{11} - (\gamma\beta)_{12} - (\gamma\beta)_{13} + (\gamma\beta)_{23} \\ (\gamma\beta)_{21} - (\gamma\beta)_{22} - (\gamma\beta)_{13} + (\gamma\beta)_{23} \end{bmatrix}.$$

Addressing the issue of parameter estimation and thereby attempting to find the most parsimonious form of the model to fit the data, the following set of hypotheses will be tested:

(6-12a) H_o: $\gamma_1 = \gamma_2 = \gamma_3 = o$;

(6-12b) H_o: $\beta_1 = \beta_2 = o$; and

(6-12c) H_o: $(\gamma\beta)_{ij} = 0$, $i = 1,2,3$, $j = 1,2$.

This set of hypotheses is consistent with the omnibus hypotheses given by (6-1) and (6-5). Acceptance of all three hypotheses would imply that all conditional expected returns are equal to each other. The following discussion will relate these hypotheses with the five contrasts of vector $\underline{\phi}$. Furthermore, assuming no interaction effects an equivalent form of contrasts one through three will be derived, possible results of the testing will be interpreted, and estimation of parameters will be explained.

Main-Class Model

It is evident from the vector $\underline{\phi}$ that main-class and interactive effects are inextricably confounded and cannot be estimated separately. In the preliminary discussion of the contrasts, it will be assumed for east of interpretation that no interaction effects exist, i.e., (6-12c) is not rejected statistically. Under this assumption the interaction parameters are set equal to zero and the model is referred to as a main-class model. The vector $\underline{\phi}$ reduce to

$$\underline{\phi} = \begin{bmatrix} \mu + (\gamma_1 + \gamma_2 + \gamma_3)/3 + (\beta_1 + \beta_2)/2 \\ \gamma_1 - \gamma_3 \\ \gamma_2 - \gamma_3 \\ \beta_1 - \beta_2 \\ 0 \\ 0 \end{bmatrix}.$$

The contrast $\gamma_1 - \gamma_3$ equals

$$(\mu_{1.} - \mu) - (\mu_{3.} - \mu)$$

$$= (\mu_{1.} - \mu_{3.})$$

$$= (\mu_{11} + \mu_{12})/2 - (\mu_{31} + \mu_{32})/2$$

$$= [E(\tilde{R}/\tilde{\theta}_1 = H, \tilde{\theta}_2 = H) + E(\tilde{R}/\tilde{\theta}_1 = H, \tilde{\theta}_2 = L)]/2 -$$

$$[E(\tilde{R}/\tilde{\theta}_1 = L, \tilde{\theta}_2 = H) + E(\tilde{R}/\tilde{\theta}_1 = L, \tilde{\theta}_2 = L)]/2$$

$$= E(\tilde{R}/\tilde{\theta}_1 = H, \tilde{\theta}_2 = A) - E(\tilde{R}/\tilde{\theta}_2 = L, \tilde{\theta}_2 = A)$$

$$= E(\tilde{R}/\tilde{\theta}_1 = H) - E(\tilde{R}/\tilde{\theta}_1 = L).$$

This difference holds for all levels of the COP forecast error (realizations of $\tilde{\theta}_2$). The letter "A" indicates the values of $\tilde{\theta}_2$ averaged out. One could have gone directly from $(\mu_{1.} - \mu_{3.})$ to $E(\tilde{R}/\tilde{\theta}_1 = H) - E(\tilde{R}/\tilde{\theta}_1 = L)$ in this progression. The additional steps were inserted to help clarify the contrasting of this design with an alternative to be discussed later. Similarly $\gamma_2 - \gamma_3$ equals

$$(\mu_{2.} - \mu) - (\mu_{3.} - \mu)$$

$$= (\mu_{2.} - \mu_{3.})$$

$$= (\mu_{21} + \mu_{22})/2 - (\mu_{31} + \mu_{32})/2$$

$$= [E(\tilde{R}/\tilde{\theta}_1 = M, \tilde{\theta}_2 = H) + E(\tilde{R}/\tilde{\theta}_1 = M, \tilde{\theta}_2 = L]/2 -$$

$$[E(\tilde{R}/\tilde{\theta}_1 = L, \tilde{\theta}_2 = H) + E(\tilde{R}/\tilde{\theta}_1 = L, \tilde{\theta}_2 = L)]/2$$

$$= E(\tilde{R}/\tilde{\theta}_1 = M, \tilde{\theta}_2 = A) - E(\tilde{R}/\tilde{\theta}_1 = L, \tilde{\theta}_2 = A)$$

$$= E(\tilde{R}/\tilde{\theta}_1 = M) - E(\tilde{R}/\tilde{\theta}_1 = L).$$

These two contrasts will be used to test the effects that different levels of the HCI forecast error have on expected returns. If their differences are not statistically different from zero, then the null hypothesis given by (6-12a) would be accepted. This result would be consistent with $E(\tilde{R}/\tilde{\theta}_1 = H) = E(\tilde{R}/\tilde{\theta}_1 = M) = E(\tilde{R}/\tilde{\theta}_1 = L) = E(\tilde{R})$ and implies that the HCI forecast error signal reflects no information beyond that available at time t, the portfolio formation date. On the other hand, rejection of this hypothesis would imply that the HCI forecast error signal does reflect information. Furthermore, this main-class model assumption enables one to estimate these effect contrasts by directly employing the estimated marginal means of the HCI forecast error factor. These estimates are: $\hat{\gamma}_1 - \hat{\gamma}_3 = \bar{y}_{1..} - \bar{y}_{3..}$ and $\hat{\gamma}_2 - \hat{\gamma}_3 = \bar{y}_{2..} - \bar{y}_{3..}$.

The contrast $\beta_1 - \beta_2$ equals

$$
\begin{aligned}
& (\mu_{.1} - \mu) - (\mu_{.2} - \mu) \\
&= (\mu_{.1} - \mu_{.2}) \\
&= (\mu_{11} + \mu_{21} + \mu_{31})/3 - (\mu_{12} + \mu_{22} + \mu_{32})/3 \\
&= [E(\tilde{R}/\tilde{\theta}_1 = H, \tilde{\theta}_2 = H) + E(\tilde{R}/\tilde{\theta}_1 = M, \tilde{\theta}_2 = H) + \\
&\quad E(\tilde{R}/\tilde{\theta}_1 = L, \tilde{\theta}_2 = H)]/3 - [E(\tilde{R}/\tilde{\theta}_1 = H, \tilde{\theta}_2 = L) + \\
&\quad E(\tilde{R}/\tilde{\theta}_1 = M, \tilde{\theta}_2 = L) + E(\tilde{R}/\tilde{\theta}_1 = L, \tilde{\theta}_2 = L)]/3 \\
&= E(\tilde{R}/\tilde{\theta}_1 = A, \tilde{\theta}_2 = H) - E(\tilde{R}/\tilde{\theta}_1 = A, \tilde{\theta}_2 = L) \\
&= E(\tilde{R}/\tilde{\theta}_2 = H) - E(\tilde{R}/\tilde{\theta}_2 = L).
\end{aligned}
$$

This contrast will be used to test the effects that two different levels of the COP forecast error have on expected returns. If the difference is not statistically different from zero, then the null hypothesis given by (6-12b) would be accepted. This result would be consistent with $E(\tilde{R}/\tilde{\theta}_2 = H) = E(\tilde{R}/\tilde{\theta}_2 = L) = E(\tilde{R})$ and implies that the COP forecast error signal reflects no information beyond that available at time t. On the other hand, rejection of this hypothesis would imply that the COP forecast error signal does reflect information. Given the main-class assumption, the effect contrast can be estimated directly by employing the estimated marginal means of the COP forecast error. The estimate is $\hat{\beta}_1 - \hat{\beta}_2 = \bar{y}_{.1.} - \bar{y}_{.2.}$.

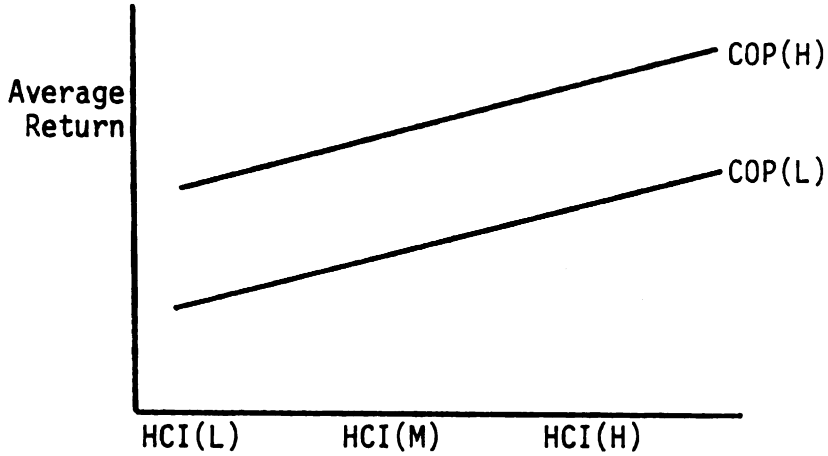
Interaction Effects

If the interaction terms in the multivariate analysis of variance are significant ((6-12c) is rejected), then the main-class model does not hold. Main class effects and interaction effect are inextricably confounded and cannot be estimated separately. In this case, the marginal means of the two-way design are not informative and analysis of cell means is necessary to interpret the interactive effects. Figure 6-2 reviews pictorially some of the possible outcomes which will be discussed next.

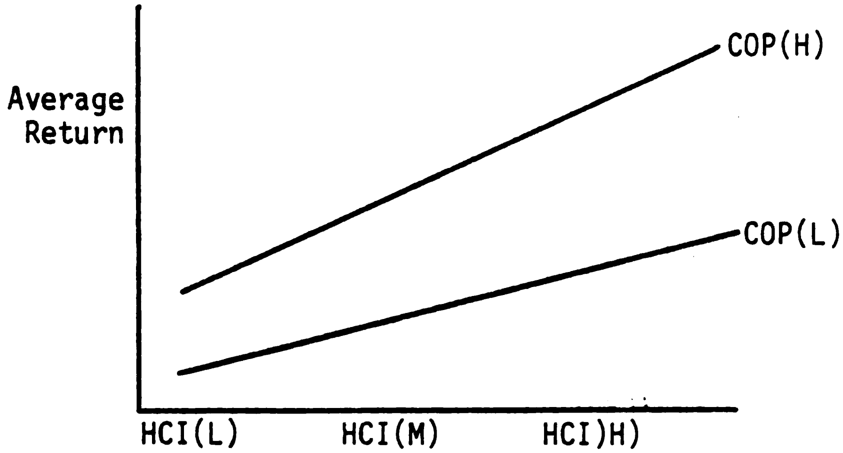
Figure 6-2a depicts the case where no interaction effect exists. Recall, this was the preliminary assumption in the discussion above. Returns associated with the high COP forecast error level are greater than the returns associated with the low COP forecast error. Since the lines are parallel, the magnitude of the difference is uniform throughout the various HCI forecast error levels. If there was no COP forecast error effect, the lines would be coincident. Figure 6-2b also depicts a case where the high COP forecast error level is associated with greater returns than the low COP forecast error level, but the difference

Figure 6-2

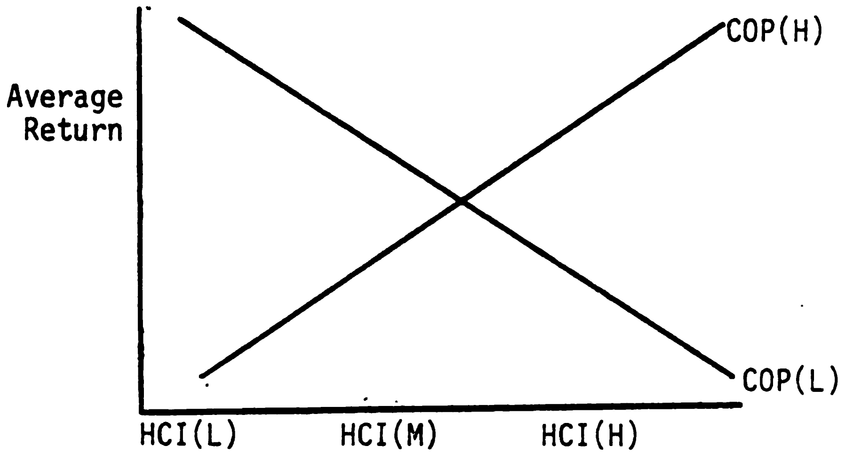
Some Possible Outcomes of a 3 x 2 Factorial Design



Solution a



Solution b



Solution c

increases throughout the HCI forecast error levels. In this case the COP forecast error effect is greater at the high HCI forecast error level than it is at the low HCI forecast error level. Therefore, the magnitude of the COP forecast error effect is dependent on the HCI forecast error level. Lines cross in Figure 6-2c depicting the case where the return associated with low COP forecast error level is greater than the return associated with high COP forecast error level at the low HCI forecast error level. The opposite condition holds at the high HCI forecast error level.

In the design discussed above, it was assumed that the two factors are crossed, i.e., every level of one of the factors appears with every level of the other factor. In a design over measures, the design should be balanced, i.e., an equal number of observations per cell (Cox [1958, p. 30]. In this type of research setting, the researcher does not have control over which firms receive the various "treatments". Therefore, if correlation exists between the two factors, the crossed design would not be balanced with respect to firms. However, the ultimate experimental units are portfolios each of which is comprised of those firms that are conditioned on a particular realization of the conditioning variables. Therefore, if it is possible to construct portfolios for each realization, then technically the crossed design would be balanced. Even if this construction is possible, it will be argued below that the design should not be treated as crossed given that a "high" degree of correlation exists.

In those cases where the two factors should not be treated as crossed, modifications resulting in a one-factor design might be appropriate for analyzing the data. Introduction of this design along with the discussion of design choice will first be presented where relational extremes exist between the two factors.

Variable Relationships and the One-Factor Design

For ease in discussing design modifications that could arise due to the degree of correlation existing between the factors, the COP forecast error will also be divided into three levels. The degree of correlation will be examined by ranking the firms twice. One ranking will be based on the HCI forecast error, while the other will be based on the COP forecast error. Each ranking will be divided into three levels (ranges): high (H), middle (M), and low (L). Given these subdivisions of each ranking, Figure 6-3 illustrates the two extreme cases that could result from assigning firms to the nine difference combinations.

Figure 6-3a-1 and 6-3a-2 depict the case where there exists an equal number of firms at each level of the COP forecast error factor for every level of the HCI forecast error factor. This implies, for example, that firms with high HCI forecast error realization might have corresponding COP forecast error realizations of either high, middle, or low. There is no relationship between the factors. Hence, the factors are both crossed and balanced, and the data analysis would proceed as discussed above.

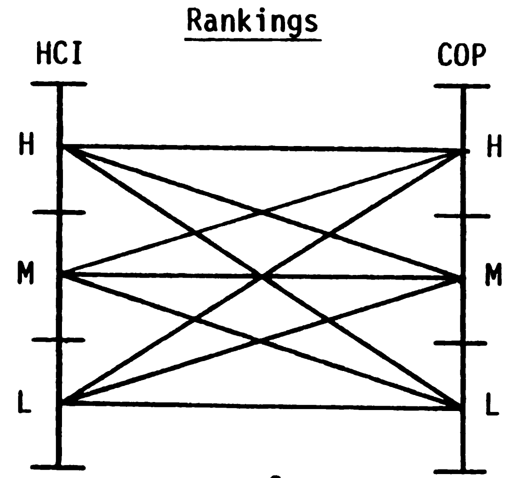
Figure 6-3b-1 and 6-3b-2 depict the case where only the "H,H", "M,M", and "L,L" level combinations (cells) have firms. This implies that firms with high HCI forecast error realizations have corresponding high COP forecast error realizations. Therefore, at this level of grouping, there exists a relationship between the two factors. Further examination of factor relationships within each cell is then necessary and leads to two additional extreme possibilities within this case.

Figure 6-3

Variable Relationships (based on 108 firms)

HCI \ COP	H	M	L
H	12	12	12
M	12	12	12
L	12	12	12

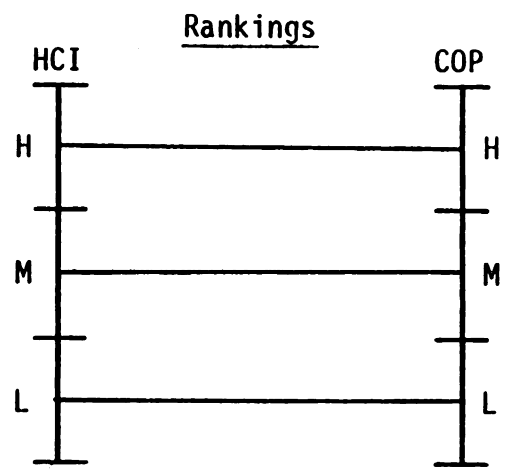
a-1



a-2

HCI \ COP	H	M	L
H	36		
M		36	
L			36

b-1



b-2

These possibilities will be discussed next.

First, if firms within each of the three cells are perfectly correlated with respect to the two factors, then these factors are perfect substitutes for each other. One factor would not reflect any information not already reflected by the other. This finding, in itself, would have important implications since it implies that the COP forecast error does not reflect information not already reflected in the HCI forecast error. Finally, if the factors are uncorrelated within these cells, further analysis might reveal that the COP forecast error signal reflects information beyond that of the HCI forecast error signal. These are the extreme cases, however, and the analysis would be made as long as the correlations within each diagonal cell are not high. Furthermore, the analysis will be made by employing a one-factor design, i.e., the two factors will be considered as one. Given the original two-level classification of the COP forecast error (i.e., H and L), the factor will have six levels with no interaction effects possible. See Figure 6-4 for a pictorial representation of this design.

In this case, factor order in the construction of portfolios becomes important in interpreting the variables of the study. Given the factor order employed in the construction above, the variables, to be analyzed are $\tilde{\theta}_1$ and $\tilde{\theta}_2/\theta_1$, rather than $\tilde{\theta}_1$ and $\tilde{\theta}_2$. The variable $\tilde{\theta}_1$ is defined as before. Whereas, $\tilde{\theta}_2/\theta_1$ is the COP forecast error given the HCI forecast error. For convenience, let $\tilde{\theta}_2' = \tilde{\theta}_2/\theta_1$. There are six different realizations of $\tilde{\theta}_2'$ (i.e., H/H, H/M, H/L, L/H, L/M, L/L). As an example, H/H would be interpreted as the COP forecast error realization being H given that the HCI forecast error realization is H.

For brevity, one might refer to the first three as H realizations

Figure 6-4

One-Factor Design

$(\tilde{\theta}_1, \tilde{\theta}_2')$	
(H, H/H)	$\bar{y}_{1.}$
(H, L/H)	$\bar{y}_{2.}$
(M, H/M)	$\bar{y}_{3.}$
(M, L/M)	$\bar{y}_{4.}$
(L, H/L)	$\bar{y}_{5.}$
(L, L/L)	$\bar{y}_{6.}$
	$\bar{y}_{..}$

Key: - denotes average

$\bar{y}_{i.}$ is the observed average portfolio return in the ith treatment for the 50 week period.

$\bar{y}_{..}$ is the observed average portfolio return for the 50 week period.

and the second three as L realizations. The reader, however, should not improperly interpret these H and L realizations as being the respective values assigned to the upper and lower ranges of the COP forecast error ranking of all firms. Instead the H and L realizations are the respective values assigned to each of three upper and lower ranges. These ranges correspond to three COP forecast error rankings, which are derived after first grouping firms according to their HCI forecast error in the portfolio construction process. In summary, it should be noted that range ordering of the realizations of $\tilde{\theta}_2'$ according to the COP forecast error ranking of all firms is H/H > L/H > H/M > L/M > H/L > L/L.

The model hypothesized for the one factor design is

(6-13) $(\tilde{R}/\underline{\theta})_{it} = \mu + \gamma_i + \tilde{e}_{it}$, $i = 1,2,\ldots,6$, $t = 1,2,\ldots,50$,

where

$(\tilde{R}/\underline{\theta})$ = the observed portfolio return in the ith treatment for week t,

μ = the grand mean,

$\gamma_i = (\mu_i - \mu)$ = the ith level HCI-COP forecast effect, and

$\tilde{e}_{it}$ = the error term.

The matrix representation of the model is given by the expression

(6-14) $\underline{Y}. = A\underline{\xi} + \underline{\varepsilon}.$,

where

$$A = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix},$$

$$\underline{\xi} = \begin{bmatrix} \mu \\ \gamma_1 \\ \gamma_2 \\ \gamma_3 \\ \gamma_4 \\ \gamma_5 \\ \gamma_6 \end{bmatrix},$$

and $\underline{\varepsilon}$. is defined as in (6-7).

The reparameterization matrix selected for this study is

$$L = \begin{bmatrix} 1 & 1/6 & 1/6 & 1/6 & 1/6 & 1/6 & 1/6 \\ 0 & 1/2 & 1/2 & -1/4 & -1/4 & -1/4 & -1/4 \\ 0 & 0 & 0 & 1/2 & 1/2 & -1/2 & -1/2 \\ 0 & 1 & -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & -1 \end{bmatrix}.$$

Premultiplying $\underline{\xi}$ by L results in

$$\underline{\phi} = \begin{bmatrix} \mu + (\gamma_1 + \gamma_2 + \gamma_3 + \gamma_4 + \gamma_5 + \gamma_6)/6 \\ (\gamma_1 + \gamma_2)/2 - \tfrac{1}{2}[(\gamma_3 + \gamma_4)/2 + (\gamma_5 + \gamma_6)/2] \\ (\gamma_3 + \gamma_4)/2 - (\gamma_5 + \gamma_6)/2 \\ \gamma_1 - \gamma_2 \\ \gamma_3 - \gamma_4 \\ \gamma_5 - \gamma_6 \end{bmatrix}.$$

The omnibus hypothesis related to the five contrasts of vector $\underline{\phi}$ is given by

(6-15) H_o: $\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = \gamma_5 = \gamma_6 = o.$

If these five contrasted differences are not statistically different from zero then the omnibus hypothesis given by (6-5) will be accepted. This would imply that neither forecast error variables reflect information. If there are, however, statistically significant differences, the resulting implications will depend on the contrasts involved.

The third, fourth, and fifth contrasts and their equivalent form are

$$\gamma_1 - \gamma_2 = E(\tilde{R}/\tilde{\theta}_1 = H, \tilde{\theta}_2' = H/H) - E(\tilde{R}/\tilde{\theta}_1 - H,\ \tilde{\theta}_2' = L/H).$$

$$\gamma_3 - \gamma_4 = E(\tilde{R}/\tilde{\theta}_1 = M, \tilde{\theta}_2' = H/M) - E(\tilde{R}/\tilde{\theta}_1 = M,\ \tilde{\theta}_2' = L/M),$$

$$\gamma_5 - \gamma_6 = E(\tilde{R}/\tilde{\theta}_1 = L, \tilde{\theta}_2' = H/L) - E(\tilde{R}/\tilde{\theta}_1 = L,\ \tilde{\theta}_2' = L/L).$$

The equivalent forms result from substitution, e.g., $\gamma_1 = E(\tilde{R}/\theta_1 =$

H, $\tilde{\theta}_2' = H/H) - \mu$. If any of their differences are significant, then the implication is that the COP forecast error signal reflects additional information to that of the HCI forecast error signal.

The first and second contrasts are comprised of three distinct components. These components and their equivalent forms are

$$(\gamma_1 + \gamma_2)/2 = E(\tilde{R}/\tilde{\theta}_1 = H, \tilde{\theta}_2' = H/H)/2 + E(\tilde{R}/\tilde{\theta}_1 = H, \tilde{\theta}_2' = L/H)/2 - \mu,$$

$$(\gamma_3 + \gamma_4)/2 = E(\tilde{R}/\tilde{\theta}_1 = M, \tilde{\theta}_2' = H/M)/2 + E(\tilde{R}/\tilde{\theta}_1 = M, \tilde{\theta}_2' = L/M)/2 - \mu,$$

$$(\gamma_5 + \gamma_6)/2 = E(\tilde{R}/\tilde{\theta}_1 = L, \tilde{\theta}_2' = H/L)/2 + E(\tilde{R}/\tilde{\theta}_1 = L, \tilde{\theta}_2' = L/L)/2 - \mu.$$

That segment of each component, other than μ, represents expected returns of portfolios. These portfolios are a simple average of two from the original six portfolios. Specifically the average of two H, two M, and two L HCI forecast error portfolios, respectively. Interpretation of any significant differences is not as straightforward as above. This is because the COP forecast error realizations for each segment do not average out and, therefore, this variable cannot be dropped as in the crossed design case. They do not average out since each pair (e.g., H/H, L/H) does not represent H and L values from the full range of COP forecast error ranked values. Recall, however, that at this level of grouping (i.e., the resulting three portfolios), firms with, for example, high (H) HCI forecast error realizations also have high (H) COP forecast error realizations. Therefore, at this level, it is possible for both forecast error variables to reflect the same information. In symbols, this is explained by

$$E(\tilde{R}/\tilde{\theta}_1 = H, \tilde{\theta}_2' = H/H)/2 + E(\tilde{R}/\tilde{\theta}_1 = H, \tilde{\theta}_2 = L/H)/2$$

$$= E(\tilde{R}/\tilde{\theta}_1 = H, \tilde{\theta}_2' = A/H)$$

$$= E(\tilde{R}/\tilde{\theta}_1 = H, \tilde{\theta}_2 = H)$$

$$= E(\tilde{R}/\tilde{\theta}_1 = H)$$

$$= E(\tilde{R}/\tilde{\theta}_2 = H).$$

(Note that $\tilde{\theta}_2'$ is replaced by $\tilde{\theta}_2$ in the third step and the H realization is based on the full range of COP forecast error ranked values.) Thus, if there are any significant differences for these two contrasts, then the implication is that either forecast error signal reflects information.

Other firm configuarations between the two extremes depicted in Figure 6-3 are possible. For example, one or more firms might exist in each off-diagonal cell without the total configuration being balanced. Thus, the crossed design would not be balanced with respect to firms. Recall, however, that the ultimate experimental unit is a portfolio. Conceptually, measures of the dependent variable for each observation (week) are assumed to be returns on a "single" portfolio where each return corresponds to a different realization of $\underline{\tilde{\theta}}$. In reality, of course, it is impossible for a single portfolio to receive six different "treatments" each week. Rather, six individual portfolios, viewed as having identical properties except for the "treatments" are employed. Since the number of weekly returns observed for each of these portfolios is equal, it is technically possible to treat the design as crossed.

Pre-experimental portfolio equivalence is essential to internal validity. Therefore, in constructing portfolios, it is important to approximate relative risk equivalence. However, this equivalence is impaired, as Gonedes explains, where the number of firms comprising each portfolio varies. In a study examining the information content of special items he states

[1975, p. 244]:

> Both the portfolio constructed for each type of special item and its matching portfolio (based upon firms reporting no special items) should have about the same number of components for each fiscal year. This is to avoid inducing heteroscedasticity; recall that the variance of a portfolio return is directly related to the number of securities in the portfolio. In addition, the number of components in the portfolio for a given type and fiscal year should have roughly the same number of components as its matching portfolio for that year. The reason for this is given in remark (R.6) in the Appendix. It is clear from table 1 that neither of these size requirements can be met without eliminating some firms from the analysis. So, firms were randomly excluded so as to satisfy those requirements.

In the appendix he states [p. 254]:

> This is important for. . .comparisons. . .of the estimated relative risks of portfolios. If the groups' sizes were not balanced, our results would be affected by the mechanical effects of different sample sizes.

Therefore, given the additional concern of portfolio equivalence, configurations that are not approximately balanced with respect to firms will not be treated as crossed.

These cases also have an impact on how the contrasts are interpreted in a one-factor design. In this regard, the following relations between COP forecast error realizations hold: H/H > L/H; H/M > L/M; and H/L > L/L. However, some realizations would contain firms from both the upper and lower ranges of the COP forecast error ranking of all firms. For example, L/H might contain firms in the lower range, whereas H/L might contain firms in the upper range. Therefore, one cannot interpret the effect of averaging over two conditional COP forecast error realizations (e.g., H/H and L/H), in the same manner as when all firms fall on the diagonal. Thus, the variables are not perfect substitutes at this level of grouping. Accordingly, if there are any significant differences for the two HCIFE contrasts, interpretable implications are restricted to HCIFE variable.

Comparison of Design Implementation

The two designs discussed above are adaptations of a design developed by Gonedes [1978]. He examined the information contents of earnings, dividends, and extraordinary items. The primary variable of interest in this study was not included in his set. In addition, there are three major design implementation differences. Each of these differences will be discussed within the context of the variables examined here.

Following Gonedes' method of implementation, one would first test the omnibus hypothesis given by (6-1) to determine whether there exists any significant difference in expected portfolio returns. If the null hypothesis is rejected, further exploration would be made into which forecast error realizations probably contributed to this rejection. This, of course, is the primary objective of the research effort. The exploration would be made by formulating appropriate _post hoc_ contrasts of interest. Mechanically, these contrasts are constructed by assigning specific values to the components of the vector $\underline{w}$ in (6-1). These contrasted differences would then be tested for significance.

The hypotheses that are introduced as _post hoc_ contrasts after rejecting the omnibus hypothesis could, however, be introduced as _a priori_ contrasts and tested initially. In this study, _a priori_ contrasts are introduced through the reparameterization process. The advantage to this procedure is that it provides more powerful tests (and shorter conficence intervals) for these contrasts than the classical omnibus approach. This is desirable because increasing power of the tests, increases the probability of detecting differences when in fact they exist.

Gonedes' approach would also involve construction of control portfolios to be arbitrarily paired with the information portfolios. The portofolio pairs would be used to estimate each of the six components of the expected means difference vector $\underline{\mu}_d$ in (6-1). However, the effect of these control portfolios are cancelled out when the _post hoc_ contrasts are formed. For example, $[E(\tilde{R}/\tilde{\theta}_1 = H,\tilde{\theta}_2 = H) - E(\tilde{R})] - [E(\tilde{R}/\tilde{\theta}_1 = H,\tilde{\theta}_2 = L) - E(\tilde{R})] = E(\tilde{R}/\tilde{\theta}_1 = H,\tilde{\theta}_2 = H) - E(R/\tilde{\theta}_1 = H,\tilde{\theta}_2 = L)$.

For clarity, an equivalent statement of the hypothesis given by (6-1) was introduced in this study. This statement given by (6-5) hypothesizes that all conditional expected returns are equal to each other. Since unconditional expected returns are not included in this formulation, control groups are not needed to estimate their values. Even if (6-1) had been solely relied upon in formulating the original model, control groups still would not have been necessary. As with _post hoc_ contrasts, their effects are cancelled out when the _a priori_ contrasts are formed during the reparameterization process. Elimination of this need for control portfolios avoids problems that might arise in their construction and increases the power of the test. For a thorough discussion of this issue see Appendix A.

The most important difference between approaches is that consieration is given here to relationships between "information" variables. This is essential since appropriate design choice and interpretation of results is dependent on these relationships. In his study, Gonedes does not present the correlations between his "information" variables. His interpretation of test results on the _post hoc_ contrasted differences would lead one to assume that the variables are crossed and balanced. This is because he averages out variables upon forming contrasts. If, in fact, variable relationships justify this assumption, then a two (three in his design) factor crossed design would have been warranted. This design would have allowed testing of the interaction effects. Furthermore, if the results are consistent with a main-class model, one could then estimate the contrasted effects each "information" variable has on expected returns. His overall approach, however, is consistent with a one-factor design. This design would be appropriate when variable realtionships prohibit one from assuming variables are crossed. This in turn, requires a different interpretation of the test results as discussed above.

FOOTNOTES TO CHAPTER VI

[1] Morrison [1967] provides a detailed discussion of this test statistic.

[2] See Bock [1975] for a thorough development of the models and many of the procedures discussed in this chapter.

CHAPTER VII

EMPIRICAL RESULTS

Relationship Between Conditioning Variables

The sequential portfolio construction procedure results in portfolios comprised of an equal number of firms; i.e., the portfolios are balanced. It is this balanced construction that enhances pre-experimental equivalence among the information portfolios.

Recall, that in this construction, all firms are initially ranked according to their HCI forecast errors and then divided into three non-overlapping groups: high (H), middle (M) and low (L). The firms in each of these groups are ranked according to their COP forecast errors and then divided into two groups: high (H) and low (L). This procedure results in six different information groups, each containing eighteen firms. An inherent facet of this procedure is that the COP forecast error values are conditioned on HCI forecast error values. For example, $\theta_2' = \theta_2/\theta_1 = L/H$, where θ_2 is the COPFE realization and θ_1 is the HCIFE realization. However, this aspect of the process does not imply that an actual relationship exists between the two variables.

Determination of this relationship between the two variables is necessary for the selection of an appropriate design. Recall that the following two relational extremes are possible: (1) the variables are independent or (2) the variables are perfectly correlated. If the first extreme exists, then a two-factor crossed design would be employed. The portfolio construction process does not deter implementation of this design, since independence negates the conditioning aspect of the procedure. For example, $\theta_2' = \theta_2/\theta_1 = L/H$ is equivalent to $\theta_2' = \theta_2 = L$.

If minor departures from equal cell size exist, modifications at the pre-portfolio construction stage can be made to accommodate implementation of the two-factor design (i.e., random elimination of firms from the over-populated cells). If the second extreme exists, then analysis of a single variable's realizations is sufficient for investigating the information effect of the other. This is true, since the two variables are perfect substitutes for each other. Intermediate relationships would require the use of a one-factor design.

The relationship that exists between the two variables is tested first by using each variable's raw scores (i.e., its calculated quantitative forecast errors) obtained from the one hundred and eight sample firms. The calculated Pearson product-moment correlation is .6698 and the probability of making a Type I error in rejecting the hypothesis of no association is zero. From this result it is inferred that correlation exists between the variables, although not a perfect one.

Recall, however, that conditioning variables are not treated quantitatively. Rather, the raw scores are grouped and $\tilde{\theta}_1$ and $\tilde{\theta}_2$ are treated as ordinal scale variables. With respect to analyzing the relationship that exists between $\tilde{\theta}_1$ and $\tilde{\theta}_2$, the full range of COP forecast errors are trichotomized for clarity. Therefore, at this level of grouping both variables can assume anyone of three values, namely, high (H), middle (M) and low (L).

Given this partitioning on an ordinal scale, one must examine the joint frequency distribution of cases (firms) according to the two conditioning variables in order to determine the nature of the relationship. The three levels for each variable result in a (3 x 3) contingency table. The test of association employed is Kendall's Tau b. This statistic takes on the value of + 1 when all firms fall on the major diagonal and - 1 when all firms fall on the minor diagonal. If each cell frequency is equal (implying no association), then the Tau b value is zero.

The observed sample frequencies (percentages) are shown in Table 7-1. The calculated Tau b is .32587 and the probability of rejecting the null hypothesis of no association is .0001. Not unexpectedly, the statistical result (at this level of grouping) also reveals a positive relationship, although not a perfect one. Furthermore, visual inspection of the contingency table reveals a pattern of cell frequencies consistent with the statement that neither relational extreme exists. However, the existence of a positive relationship is supported by the largest firm frequencies occurring on the major diagonal. These diagonal frequencies (percentages) are HH = 23 (21.3), MM = 19 (17.4), and LL = 23 (21.3). The smallest cell frequency of 3 (2.8) occurs in HL (column value given first). Overall, the degree of association revealed does not appear to be exceedingly strong. However, departures from equal cell size are deemed excessive for employment of the two-factor crossed design. Accordingly, the one-factor design is employed to test the information hypothesis.

Mixed-Model Assumption

Traditionally, the univeriate mixed model was used to analyze information portfolio returns. The advantage of this model is that it provides a more powerful test than the multivariate model. However, the assumption of independence of error terms (i.e., zero covariances after transformation[1]) is essential for proper implementation of the mixed-model. See Bock [1975, pp. 449-460] for a complete model description.

Table 7-1

Contingency Table For Sample Firms

COPFE \ HCIFE	H	M	L	Row Total
H	23 (21)*	7 (6)	6 (6)	36
M	10 (9)	19 (18)	7 (6)	36
L	3 (3)	10 (9)	23 (21)	36
Column Total	36	36	36	108

Kendall's Tau b = .32587: Significance = .0001

* Percentage of total firms

The determinant of the correlation matrix given by

$$(7\text{-}1) \quad \Lambda = |\mathrm{Corr}(N-1)P'\Sigma P|$$

provides the likelihood-ratio criterion for testing the hypothesis that $P'\Sigma P$ is diagonal against a general alternative. Percentage points of the null distribution of (7-1) are well approximated by equating

$$(7\text{-}2) \quad -[(N-1) - (2p + 5)/6]\ln\Lambda$$

to the central χ^2 distribution on $[p(p-1)]/2$ degrees of freedom, where p is the number of dependent variables and N is the number of observations. Significance of this χ^2 rejects the hypothesis that $P'\Sigma P$ is a diagonal matrix.

The calculated value of (7-2) based on the sample error correlation matrix in Table 7-2 is 1.03. This result is consistent with the assumption of independence of error terms for the transformed observations. Therefore, the mixed-model approach is deemed to be appropriate for testing the data. Thus, the univariate F-tests for each contrast are statistically independent, and the overall error rate may be calculated by (3-5). Except for the computational format, multivariate analysis of variance can be adapted to provide the same analysis as the univariate mixed-model. However, as discussed below the resultant increase in power does not appear to noticeably affect the results.

Test Results of the Information Hypothesis

The *a priori* contrasts to be tested jointly are summarized in Table 7-3. Each set of weights used in their construction correspond to the last five rows of the one-factor design reparameterization matrix L. In parentheses are related normalized sets of weights. These sets

Table 7-2

Estimated Error Correlation Matrix

For Transformed Portfolio Returns

Transformations						
Constant	1.000					
Contrast 1	-.091	1.000				
Contrast 2	.076	-.259	1.000			
Contrast 3	-.425	-.021	.187	1.000		
Contrast 4	.197	-.265	.381	.099	1.000	
Contrast 5	.170	.378	-.064	-.121	-.222	1.000

Calculated χ^2 (15) = 1.03

Alpha Points	Value of χ^2 (15)
.100	22.31
.050	25.00
.025	27.49
.010	30.58

Table 7-3

Portfolio Weights and Resultant Contrasts

7-3a. -- Sets of Weights Applied to Portfolios to Form Contrasts

Portfolio	Conditioning Realization $(\theta_1,\theta_2/\theta_1)$	Sets of Weights (Normalized) (1)	(2)	(3)	(4)	(5)
1	H,H/H	$1/2(\sqrt{3}/3)$		$1(\sqrt{2}/2)$		
2	H,L/H	$1/2(\sqrt{3}/3)$		$-1(-\sqrt{2}/2)$		
3	M,H/M	$-1/4(-\sqrt{3}/6)$	$1/2(1/2)$		$1(\sqrt{2}/2)$	
4	M,L/M	$-1/4(-\sqrt{3}/6)$	$1/2(1/2)$		$-1(-\sqrt{2}/2)$	
5	L,H/L	$-1/4(-\sqrt{3}/6)$	$-1/2(-1/2)$			$1(\sqrt{2}/2)$
6	L,L/L	$1/4(-\sqrt{3}/6)$	$-1/2(-1/2)$			$-1(-\sqrt{2}/2)$

7-3b. -- Resultant Contrasts

Number	Contrasts
1	1/2(H,H/H) + 1/2(H,L/H) - 1/4(M,H/M) - 1/4(M,L/M) - 1/4(L,H/L) - 1/4(L,L/L)
2	1/2(M,H/M) + 1/2(M,L/M) - 1/2(L,H/L) - 1/2(L,L/L)
3	1(H,H/H) - 1(H,L/H)
4	1(M,H/M) - 1(M,L/M)
5	1(L,H/L) - 1(L,L/L)

* Each contrast is presented employing pre-normalized weight sets.

correspond to the last five columns of the transformation matrix P presented in Figure A-1. It is the normalized set which is used in the omnibus test.

Result of the omnibus test regarding information content of both HCI and COP forecast errors are consistent with the no information hypothesis. The omnibus test statistic for the overall test period along with other summary data is shown in Table 7-4. Furthermore, the joint test result obtained from employing the mixed-model does not alter this inference. For this model, the calculated level of significance is .128. This value is insufficient to reject the omnibus null hypothesis given a critical value of .10. Notwithstanding this insignificance, the signs of the observed contrast mean values will be reviewed.

It was anticipated, constructing contrasts, that the observed mean differences would be positive, given that on a relative basis, positive weight(s) were assigned to the more favorable portfolio(s). Only three of the five mean differences reported in Table 7-4 are positive. Included in this group are contrasts (1) and (2) which are employed to test the information content of the HCI forecast errors. These two positive value outcomes are consistent with the results of previous research (e.g., Ball and Brown [1969] and Gonedes [1978]).

With respect to contrasts (3), (4), and (5), which are formulated to test mean return differences between portfolios conditioned on different COP forecast error realizations, only the reported value of the fifth contrast is positive. Although the mean differences of the other two contrasts are negative, both values are close to zero. However, since the sample data failed to reject the omnibus null hypothesis, further discussion of possible implications seems to be highly speculative

Table 7-4

Summary Statistics For Tests On The Transformed Mean

Return Vector For The Fifty Week Test Period

Contrast	10^3 x Estimated Mean	10^2 x Estimated Standard Deviation	Univeriate F	P Less Than
1	2.20	.88	3.12	.08
2	1.93	1.31	1.09	.30
3	-.93	.97	.45	.50
4	-.18	1.40	.01	.92
5	2.73	.85	5.21	.03

F (5,45) Statistic for Multivariate Test of

Equality of Means = 1.64 with P Less Than .17

Alpha Points	Value of F (1,40)	Value of F (1,60)	Value of F (5,40)	Value of F (5,60)
.100	2.84	2.79	2.00	1.95
.050	4.08	4.00	2.45	2.37
.025	5.42	5.29	2.90	2.79
.001	7.31	7.08	3.70	3.51

at best.

Contrasted mean differences and multivariate F-statistics for each of the other three test periods are summarized in Table 7-5. The test results are highly insignificant, and yet the most interesting result pertains to the twelve week test period after December 31. The sign of each contrast is as expected for both this period and the twenty-four week test period. However, the resultant level of significance is smaller for this twelve week period than for each of the other two sub-periods. Furthermore, the value of each mean difference(s) for this twelve week subperiod is greater than both the corresponding actual and absolute values of all the other test periods. One possible interpretation of this result is that the appropriate test period is twelve weeks after the fiscal year end. If this is true, two further comments are in order.

First, additional observations obtained from using a larger test period would tend to dilute the effect. This would therefore explain the lack of significance resulting from the use of the larger test periods. Secondly, the lack of significance for the twelve week subperiod may be attributable to the small number of observations since the power of the test is affected by sample size.

Table 7-5

Summary Statistics For Subperiod Tests

Period	10^3 x Estimated Contrast Mean					Multivariate F	P Less Than
	(1)	(2)	(3)	(4)	(5)		
24 Weeks Centered On December 31	1.08	1.85	1.78	.05	2.35	F(5,19)= .66	.66
12 Weeks Before December 31	-.96	1.67	-.30	-2.41	1.78	F(5,7)= .55	.73
12 Weeks After December 31	3.13	2.04	3.86	2.50	2.92	F(5,7)=1.05	.46

FOOTNOTE TO CHAPTER VII

[1]Transformation of the observed means and the transformation matrix p are discussed in Appendix A.

CHAPTER VIII

CONCLUSION

Summary

This study is designed to investigate whether both the historical cost income and current operating profit forecast error values reflect information pertinent to assessing firms' equilibrium expected returns. Specifically, the study tests the hypothesis that the expected return differences between portfolios conditioned on various realizations of these two forecast error variables are zero. Since pre-experimental equivalence is assumed to be attained by exploiting the properties of the capital asset pricing model, detection of significant differences would imply that the forecast error realizations reflect information.

This study differs from previous replacement cost research studies in its formulation of expectations. Since these other studies focused on the initial disclosure year, prior replacement cost data were not available to formulate expectations. As a consequence, they were limited to the use of historical cost data and Value Line estimates of replacement cost in deriving expectations. In contrast, forecast error values for both variables are calculated using the martingale model to obtain proxies for investors' expectations. Since only one pre-1977 COP value exists, the drift factor is assumed to be zero in calculating the 1977 COP expectation. However, theorists have argued that the current period's COP is the best estimate of the following period's COP.

Conditioning portfolio returns on various realizations of both the historical cost income and current operating profit forecast error variables necessitates an examination of the realationship between them since it is crucial to appropriate design selection and interpretation of test results. In this regard, two extreme outcomes are possible: (1) the variables are independent or (2) the variables are perfectly correlated and thus perfect substitutes for each other. Neither extreme is inferred from the sample data. However, a positive systematic relationship is detected. Accordingly, a one-factor design is deemed appropriate.

Regarding the one-factor design, the inferred variable relationship is consistent with the formulation of _a priori_ contrasts that test the following two hypotheses: (1) the COP signals do not reflect information beyond that of the HCI signals and (2) the HCI signals do not reflect information. Test results of the first hypothesis are considered important with respect to the Securities and Exchange Commission's contention that replacement cost disclosures provide information useful to investors which is not otherwise obtainable. Testing of the second hypothesis attempts to replicate the results of previous research which has shown that the HCI forecast error variable reflects information beyond that available at time t.

The test period consists of the fifty work weeks subsequent to the March 31, 1977 portfolio formation date. Tests are conducted on weekly returns pertaining to the full fifty week period as well as three subperiods. The three subperiods comprise: (1) twenty-four weeks centered at December 31, 1977, (2) twelve weeks before December 31, and (3) twelve weeks after December 31, respectively. This segmentation of the overall period is made, since all sample firms have December 31 fiscal year ends and the existence of uncertainty with respect to the event date.

Empirical results of this study constitute evidence consistent with the hypothesis that the Securities and Exchange Commission's mandated replacement cost disclosures provide no information to the market. In this regard, one might question this study's conclusion since misspecification of the expectation models, choice of the time period and sample size, together with the use of *ex post* data to calculate *ex ante* expectations may have prevented detection of an effect. It is suggested, however, that the results in conjunction with those of other studies, each of which have utilized diverse procedures, contribute to the body of evidence necessary to the formulation of a compelling case.

Methodological procedures employed are largely adaptations of Gonedes' work. Several extensions of his methodology are introduced and believed to be of value. In testing the information content of an accounting random variable, the difference in total returns metric introduced by Gonedes has been compared to the residual return metric. This comparison has been made within the framework of maximizing the power of all tests. Maximization is accomplished by employing the statistical procedure that tests jointly the contrasts of interest to the researcher, *a priori*. To provide a setting for formulating these contrasts when investigating the information content of more than one realization of an accounting variable, the general linear model from extant statistical theory has been introduced. This model has been shown to be equivalent to the two-factor, zero-beta model and its reparameterization results in the *a priori* contrasts of interest.

The simplest contrast is the difference between two returns. As a consequence, it has been shown within a one-asset, one-period conceptual setting that the econometric properties of both metric approaches are identical. Thus, this choice between the two within an empirical setting should only be contingent upon the assumption that the expected returns of two or more securities (portfolios) are equal if their systematic risk parameters are equal. In the market based research context, there is yet a further consequence of using a priori contrasts. Forming the difference in total returns metric, this procedure has been shown to eliminate the necessity of employing an unconditional return to extinguish variability attributable to the economy-wide factor. Correspondingly, it has been shown that this elimination increases the power of the test.

The most important extension is the explicit consideration given to the relationships between accounting variables. This is essential in studies employing more than one accounting variable, since appropriate design choice and interpretation of results is dependent on their relationships. If, in fact, variables are independent, then an n-factor crossed design is warranted. This design allows explicit testing of the interaction (joint) effects. Furthermore, if the results are consistent with a main-class model (i.e., interactions effects are inferred to be zero), one could then estimate the contrasted effects each accounting variable has on expected returns. On the other hand, if systematic relationships exist, although not perfect ones, then a one-factor design is employed. This in turn, requires a different interpretation of test results.

Recommendations For Future Research

The empirical phase of this study is subject to one primary line of criticism. The test periods include data from only one year and hence provide a small number of observations. This is particularly true regarding the subperiods tested. Furthermore, demands for an increased sample size requirement are intensified by the relatively large number of parameters estimated and hypotheses tested. The reason for using just one year in examining the information content of the two forecasts error variables is attributable to the availability of data at the time the study was initiated. Of course, one possible remedy that can be incorporated in future studies is to increase the number of years included in the test periods. However, another possibility is the use of daily rather than weekly returns. The methodological refinements which have been presented are recommended for all studies investigating the information content of a random accounting variable or a vector of such variables.

APPENDICES

APPENDIX A

COMPARATIVE ANALYSIS, "CLASSICAL" CONTROL GROUPS AND THE REPARAMATERIZATION PROCESS

Comparative analysis is used to measure difference(s) in the effects of two or more treatments. If the researcher is concerned with the effect of only one treatment, then a control group (i.e., a group receiving no treatment) would be formed. The control would be considered a "treatment" enabling the researcher to make the comparative analysis. In general, however, the researcher is concerned with analyzing more than one treatment.

Analyzing more than one treatment, the presentation will be made in the context of market based research. In this context, treatments are considered to be different realizations of the information random variable $\tilde{\theta}$. The metric to be employed is the difference in total returns discussed in Chapter III. Recall, that this metric was designed to eliminate from the total return metric any variability attributable to $\tilde{R}_m$.

In the two treatment case, let θ_i and θ_j be the two realizations of $\tilde{\theta}$. Testing the null hypothesis given by (3-3) that the two expected conditional returns are equal, it was demonstrated in Chapter III that the appropriate test, (3-20), employed the difference in total returns metric. Specifically, the metric's standard deviation and an estimate of its expected value form the test denominator and numerator, respectively. The use of controls, which are in this context unconditional returns on portfolios, will be reviewed next.

Employment of these controls in the two realization case would result in forming differences by matching against each conditional return an unconditional return and then taking the difference of the differences. This is redundant! In symbols,

$$\text{(A-1)}\quad [(\tilde{R}_z/\theta_i) - \tilde{R}_{c1}] - [(\tilde{R}_q/\theta_j) - \tilde{R}_{c2}]$$

$$= [((1 - \beta_z)\tilde{R}_o + \beta_z\tilde{R}_m + \gamma_i + \tilde{\mu}_z) - ((1 - \beta_{c1})\tilde{R}_o + \beta_{c1}\tilde{R}_m + \tilde{\mu}_{c1})]$$

$$- [((1 - \beta_q)\tilde{R}_o + \beta_q\tilde{R}_m + \gamma_j + \tilde{\mu}_q) - ((1 - \beta_{c2})\tilde{R}_o + \beta_{c2}\tilde{R}_m + \tilde{\mu}_{c2})]$$

$$= [((1 - \beta_z)\tilde{R}_o + \beta_z\tilde{R}_m + \gamma_i + \tilde{\mu}_z) - ((1 - \beta_q)\tilde{R}_o + \beta_q\tilde{R}_m + \gamma_j + \tilde{\mu}_q)]$$

$$- [((1 - \beta_{c1})\tilde{R}_o + \beta_{c1}\tilde{R}_m + \tilde{\mu}_{c1}) - ((1 - \beta_{c2})\tilde{R}_o + \beta_{c2}\tilde{R}_m + \tilde{\mu}_{c2})]$$

$$= [(\gamma_i - \gamma_j) + (\tilde{\mu}_z - \tilde{\mu}_q)] + (\tilde{\mu}_{c1} - \tilde{\mu}_{c2}).$$

As a consequence, this usage results in the additional error term $(\tilde{\mu}_{c1} - \tilde{\mu}_{c2})$ in contrast to the case where controls are not employed.

The expected value of the difference in total returns metric is $\gamma_i - \gamma_j$ with or without the employment of control portfolios. However, the researcher pays a price for this redundancy because the variance with controls is greater than the variance without controls. In presenting the proof, it will be assumed that all error variances are equal and depicted by σ_μ^2. Furthermore, all error covariances are assumed equal and will be expressed as $\rho_\mu\sigma_\mu^2$, where ρ_μ is the correlation coefficient.

In the non-control approach the variance is given by

$$\text{(A-2)}\quad \mathrm{Var}(\gamma_i - \gamma_j + \tilde{\mu}_z - \tilde{\mu}_q) = 2\sigma_\mu^2(1 - \rho_\mu).$$

Whereas, under the control approach the variance is given by

$$\text{(A-3)}\quad \mathrm{Var}(\gamma_i - \gamma_j + \tilde{\mu}_z - \tilde{\mu}_q + \tilde{\mu}_{c1} - \tilde{\mu}_{c2}) = 4\sigma_\mu^2(1 - \rho_\mu).$$

The variance in (A-3) is twice as large as the variance in (A-2) for all values of ρ_μ except, of course, the value of one. In that case both variances are zero.

Examining cases with more than two realizations, for example three realizations, involves an additional complication. Letting θ_k be the third realization, the null and alternative hypotheses would then be

(A-4) H_0: $E(\tilde{R}_z/\theta_i) = E(\tilde{R}_q/\theta_j) = E(\tilde{R}_p/\theta_k)$, and

(A-4') H_1: H_0 is false.

To test for differences in these expected values jointly and thereby control Type I error rates, procedures such as ANOVA or MANOVA would be employed. However, as presently formulated, the metric employed would be the total return metric. This metric contains "undesired" variability attributable to the factor $\tilde{R}_m$ and therefore reduces the power of the test. Gonedes [1978] solves this problem by matching against each conditional portfolio return a control portfolio. By matching, he creates the difference in total returns metric. In summary, his procedure accomplishes both of the following objectives: (1) eliminates variability attributable to $\tilde{R}_m$ by employing the difference in total returns metric and (2) controls the error rate by comparing differences using a joint test. Both of these objectives increases the power of the omnibus testing procedure.

This paper proposes another approach to accomplish both of these goals. This approach is presented within the framework of the GLRM associated with the ANOVA and MANOVA testing techniques. Using this model, one formulates a priori contrasts through the reparamaterization process. (See Chapter VI pages 69 and 82). The entire process involves three steps. Although step 1 and part of step 2 are presented in Chapter VI, for continuity of thought all steps will be presented below:

Step 1 - Formulation of the GLRM

Model 1 is the GLRM in matrix form and is given by

(A-5) $$\underline{y}. = A\underline{\xi} + \underline{\varepsilon}.$$

where

$\underline{y}.$ = the vector of observed total return means,

A = the design matrix,

$\underline{\xi}$ = the vector of parameters, and

$\underline{\varepsilon}$ = the random error vector which is assumed to be distributed $N(0,\Sigma)$.

Step 2 - Reparameterization of the GLRM

The purpose of the reparameterization process is to reduce the number of unknown parameters so that the new set of parameters equals the number of equations in the model. This new set of parameters are a linear combination of the old set and they allow for a unique solution. Furthermore, by selecting the appropriate reparameterization matrix L, the new parameters will represent the *a priori* contrast of interest to the researcher. Reparameterization is achieved by factoring the design matrix into the product of two matrices (i.e., A = KL), where L is the row basis of A and K is the column basis. The derivation of model 2 is given by

(A-6) $$\begin{aligned}\underline{y}. &= A\underline{\xi} + \underline{\varepsilon} \\ &= (KL)\underline{\xi} + \underline{\varepsilon}.\end{aligned}$$

$$= K(L\underline{\xi}) + \underline{\varepsilon}.$$

$$= K\underline{\phi} + \underline{\varepsilon}. ,$$

where

$\underline{\phi}$ = the vector of new parameters,

$L = (K'K)^{-1}KA$, and

$K = AL'(LL')^{-1}$

Let

$$Q \equiv \underline{\varepsilon}.' \underline{\varepsilon}. = (\underline{y}. - K\underline{\phi})'(\underline{y}. - K\underline{\phi}),$$

then differentiating yields

$$\partial Q/\partial\phi = -2K\underline{y}. + 2K'K\underline{\phi}$$

Equating $\partial Q/\partial\phi$ to the null vector yields the normal equations used for the least squares estimation. They are given as

$$K'K\hat{\underline{\phi}} = K\underline{y}. \text{ , or}$$

$$\hat{\underline{\phi}} = (K'K)^{-1}K\underline{y}. \text{ ,}$$

where

$$E(\hat{\underline{\phi}}) = \underline{\phi} \text{ , and}$$

$$\mathrm{Var}(\hat{\underline{\phi}}) = (K'K)^{-1}\Sigma \text{ .}$$

<u>Step 3 - Orthonormalization of the Reparameterized GLRM</u>

Let $\underline{\phi} = T'\underline{\psi}$, where $K'K = T'T$ and T is called the Cholesky factor. It results from the triangular decomposition of K'K. Furthermore, if K is column-wise orthogonal[1] and the design is balanced (equal cell size), then the Cholesky is a diagonal matrix (i.e. T = T'). The derivation of model 3 is given by

$$\text{(A-7)} \qquad \begin{aligned} \underline{y}. &= K\underline{\phi} + \underline{\varepsilon}. \\ &= KI\underline{\phi} + \underline{\varepsilon}. \\ &= K[(T')^{-1}T']\underline{\phi} + \underline{\varepsilon}. \\ &= [K(T')^{-1}][T'\underline{\phi}] + \underline{\varepsilon}. \\ &= P\underline{\psi} + \underline{\varepsilon}. \end{aligned}$$

where K is orthonormalized by the inverse of the transpose of the Cholesky factor. The resulting matrix P is orthonormal, i.e. PP' = I (see figure A-1). Furthermore, $\underline{y}.$ can be transformed as

$$\text{(A-8)} \qquad \begin{aligned} P'\underline{y}. &= P'P\underline{\psi} + P'\underline{\varepsilon}. \\ &= \underline{\psi} + \underline{\varepsilon}.^{*}, \end{aligned}$$

where $\underline{\varepsilon}.^{*} \sim N(0, P'\Sigma P)$. Therefore,

$$\hat{\underline{\psi}} = P'\underline{y}.,$$

where

$$E(\hat{\underline{\psi}}) = \underline{\psi} = T'\underline{\phi}.$$

Thus,

$$\hat{\underline{\phi}} = (T')^{-1}\hat{\underline{\psi}}.$$

The transformation matrix P transforms the observed total return means. Moreover, this transformation process will yield a new set of observed means which are a linear combination of the old set. For each combination, except the first, the coefficients will add to zero. This implies that each of the components of the new set which are associated

Figure A-1

The K, $(T')^{-1}$, and P Matrices For The One-Factor Case

$$K = \begin{bmatrix} 1 & 2/3 & 0 & 1/2 & 0 & 0 \\ 1 & 2/3 & 0 & -1/2 & 0 & 0 \\ 1 & -1/3 & 1/2 & 0 & 1/2 & 0 \\ 1 & -1/3 & 1/2 & 0 & -1/2 & 0 \\ 1 & -1/3 & -1/2 & 0 & 0 & 1/2 \\ 1 & -1/3 & -1/2 & 0 & 0 & -1/2 \end{bmatrix}$$

$$(T')^{-1} = \begin{bmatrix} 1/\sqrt{6} & 0 & 0 & 0 & 0 & 0 \\ 0 & \sqrt{3}/2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sqrt{2} & 0 & 0 \\ 0 & 0 & 0 & 0 & \sqrt{2} & 0 \\ 0 & 0 & 0 & 0 & 0 & \sqrt{2} \end{bmatrix}$$

$$P = K(T')^{-1} = \begin{bmatrix} 1/\sqrt{6} & \sqrt{3}/3 & 0 & \sqrt{2}/2 & 0 & 0 \\ 1/\sqrt{6} & \sqrt{3}/3 & 0 & -\sqrt{2}/2 & 0 & 0 \\ 1/\sqrt{6} & -\sqrt{3}/6 & 1/2 & 0 & \sqrt{2}/2 & 0 \\ 1/\sqrt{6} & -\sqrt{3}/6 & 1/2 & 0 & -\sqrt{2}/2 & 0 \\ 1/\sqrt{6} & -\sqrt{3}/6 & -1/2 & 0 & 0 & \sqrt{2}/2 \\ 1/\sqrt{6} & -\sqrt{3}/6 & -1/2 & 0 & 0 & -\sqrt{2}/2 \end{bmatrix}$$

with the _a priori_ contrasts parameters of direct interest to the researcher have been transformed into differences in total mean returns. Whereas, the combination forming the first component has equal coefficients and its associated contrast parameter can be viewed as the expected market return. Estimating and testing this parameter is not a part of the researcher's omnibus hypothesis.

Before concluding, a formal consolidated analysis of the issues will be presented. The statistical test employed is Roy's largest-root criterion, which in this case equals Hotelling's T^2 (Bock [1975, pp. 150-152]). This test criterion can be expressed as the largest root λ^* of

(A-9) $|S_h - \lambda S_e| = 0,$

where

S_h = the sum of squares and cross products matrix (SSCP) for the hypothesis based on N independent observations,

S_e = the SSCP matrix for the error, and

λ = the Lagrangian multiplier.

These two matrices can be viewed as the multivariate counterparts to the univariate ANOVA sum of squares between and sum of squares within partitions of the sum of squares total. Their expected values are $(\Sigma + N\,\underline{T}\,\underline{T}')$ and $(N - 1)\Sigma$, respectively (Bock [1975, p. 458]). In addition, the vector of independent variables $\underline{y}_i$ will be expressed as residual returns. Therefore, $\underline{T}$ is the vector of expected conditional residual returns and Σ is the SSCP error matrix. More formally,

(A-10) $\underline{y}_i = \underline{T} + \underline{\varepsilon}_i$, and

(A-11) $1/N(\sum_{i=1}^{N} \underline{y}_i) = \underline{y}. = \underline{T} + \underline{\varepsilon}.$

where $\underline{y}_i$ = the (r x 1) vector of dependent variables for the i^{th} subject, i = 1,2,...,n, where each dependent variable (measure) is (ε/θ_j), j = 1,2,...,r,

$\underline{T}$ = the (r x 1) vector of expected values, where each expected value is γ_j, j = 1,...,r,

$\underline{\varepsilon}_i$ = the (r x 1) vector of sampling errors distributed $N(0,\Sigma)$.

Substituting the expected SSCP matrices results in

$$\text{(A-12)} \quad |(\Sigma + N\,\underline{T}\,\underline{T}') + \lambda[(N - 1)\Sigma]| = 0$$

The largest root λ^* is equal to T^2. Thus, statistically, this is equivalent to the approach given by (6-3) which was employed by Gonedes [1978].

Using the GLRM approach, recall that the reparameterization process results in the following transformations

$$\text{(A-13)} \quad P'\underline{y}. = P'\underline{T} + P'\underline{\varepsilon}. = \underline{\psi} + P'\underline{\varepsilon}. \ ,$$

where $P'\underline{T}$ equals $\underline{\psi}$. Furthermore,

$$\text{(A-14)} \quad S_h^* = P'(\Sigma + N\,\underline{T}\,\underline{T}')P \text{ and}$$

$$\text{(A-15)} \quad S_e^* = (N - 1)P'\Sigma P \ ,$$

where $P'P = I$. The impact that this transformation has on the test criterion is explored below.

$$\begin{aligned} \text{(A-16)} \quad 0 &= |[P'(\Sigma + N\,\underline{T}\,\underline{T}')P] - \lambda_1[(N - 1)P'\Sigma P]| \\ &= |P||[P'(\Sigma + N\,\underline{T}\,\underline{T}')P] - \lambda_1[(N - 1)P'\Sigma P]||P'| \\ &= |PP'(\Sigma + N\,\underline{T}\,\underline{T}')PP' - \lambda_1[(N - 1)PP'\Sigma PP']| \\ &= |[I(\Sigma + N\,\underline{T}\,\underline{T}')I] - \lambda_1[(N - 1)I\Sigma I]| \end{aligned}$$

$$= |[\Sigma + N\,\underline{T}\,\underline{T}'] - \lambda_1[(N-1)\Sigma]| \; .$$

Therefore, $\lambda_1^* = \lambda^*$, since the transformation does not change the determinant.

The discussion to this point has assumed the use of the residual return metric. For comparison let $\underline{v}.$ be a vector of observed total conditional return means and $\underline{\omega}$ be the vector of expected conditional total returns. More formally, each of the respective vector components is given by

$$\text{(A-17)} \quad V_{\cdot j} = (1 - \beta_z)\tilde{R}_o + \beta_z\tilde{R}_m + \gamma_j + \mu'_{\cdot j}$$

$$= (\chi_j + \mu''_{\cdot j}) + (\gamma_j + \mu'_{\cdot j})$$

$$= (\chi_j + \gamma_j) + (\mu''_{\cdot j} + \mu'_{\cdot j})$$

$$= \omega_j + \mu_{\cdot j} \text{ for } j = 1,\ldots,r$$

and in vector notation

$$\text{(A-18)} \quad \underline{V}. = \underline{\omega} + \underline{\mu}. \; ,$$

where $\underline{\mu}. \sim N(0,\Sigma_\mu)$.

After transformation, both matrices $P'\underline{\omega}\,\underline{\omega}'P$ and $P'\Sigma_\mu P$ differ from matrices $P'\underline{T}\,\underline{T}'P$ and $P'\Sigma P$, respectively, in only the first row and column. By partioning each matrix into upper (1 x 1) and lower [(r - 1) x (r - 1)] matrices, then $(P'\underline{\omega}\,\underline{\omega}'P)_{r-1}$ is identical to $(P'\underline{T}\,\underline{T}'P)_{r-1}$ and $(P'\Sigma_\mu P)_{r-1}$ is identical to $(P'\Sigma P)_{r-1}$. This is true because the transformation matrix P transforms the last (r-1) components in both $\underline{\omega}$ and $\underline{T}$ and their corresponding error terms $\underline{\mu}.$ and $\underline{\varepsilon}.$ into return differences. To clarify, recall that the only difference between the residual and total return metrics is the economy-wide component contained in the latter. The transformation matrix, however, removes this component in the (r - 1) partitioned matrices since the coefficients of each of the (r - 1) transformations equal zero. Furthermore, either of the partitioned matrices $(P'\underline{\omega}\,\underline{\omega}'P)_{r-1}$ or $(P'\underline{T}\,\underline{T}'P)_{r-1}$ can be tested directly and both represent the omnibus hypothesis of interest. Therefore, in cases involving more than two realizations the residual return metric approach is equivalent to the difference in total returns metric approach.

The use of control portfolios is thought to have a specific function in market based research. This function is to reduce variability by creating a difference in total returns metric. It has been shown in cases involving more than one realization of $\tilde{\theta}$ that this is unnecessary. Therefore, in market based research, as in general, control groups enable the researcher to determine the absolute effects of each treatment, but are entirely unnecessary for determining difference(s) in effects between treatments.

FOOTNOTE TO APPENDIX A

[1]Two vectors are orthogonal if their inner product equals zero.

APPENDIX B

INDUSTRIES OF SAMPLE FIRMS

SIC Code	Industry	Firm Frequency Number
1000	Metal Mining	1
1520	General Building Contractors	1
1600	Construction - Not Building Construction	1
2020	Dairy Products	1
2046	Wet Corn Milling	1
2065	Candy and Other Confectionery	1
2085	Distilled Rectif Blend Beverage	1
2086	Bottled - Canned Soft Drinks	2
2200	Textile Mill Products	3
2270	Floor Covering Mills	1
2300	Apparel and Other Finished Products	1
2400	Lumber and Wood Products	1
2600	Paper and Allied Products	3
2649	Convert Paper-Paperbd Pd. Nec.	2
2650	Paperboard Containers - Boxes	1
2731	Books - Publishing and Printing	1
2750	Commercial Printing	1
2800	Chemicals and Allied Products	5
2820	Plastic Matr. and Synthetic Resin	1
2830	Drugs	1
2844	Perfumes Cosmetics Toil Prep.	1
2850	Paints - Varnishes - Lacquers	1
2860	Industrial Organic Chemicals	1
2890	Misc. Chemical Products	2
2911	Petroleum Refining	3
3000	Rubber and Misc. Plastics Products	2
3241	Cement Hydraulic	3
3270	Concrete Gypsum and Plaster	1
3290	Abrasive Asbestos and Misc. Mis	1
3310	Blast Furnaces and Steel Works	1
3341	Second Smelt - Refin Nonfer Mt.	1
3350	Rolling and Draw Nonfer Metal	1
3510	Engines and Turbines	1
3531	Construction Machinery and Equipment	1
3540	Metal Working Machinery and Equipment	1
3550	Special Industry Machinery	2
3560	General Industrial Machinery and Equipment	1
3570	Office Computing and Accounting Machinery	1
3600	Elec and Electr Machinery Equipment and Supplies	1
3610	Elec. Transmission and Distr. Equipment	2
3622	Industrial Controls	1
3630	Household Appliances	1
3662	Radio - T.V. Transmitting Equipment - AP	1
3699	Electrical Machinery and Equipment NEC	1

SIC Code	Industry	Firm Frequency Number
3714	Motor Vehicle Parts - Accessories	1
3721	Aircraft	1
3728	Aircraft Parts and Aux. Equip.	1
3740	Railroad Equipment	1
3861	Photographic Equipment and Supplies	1
4011	Railroads - Line Haul Operating	1
4511	Air - Transportation - Certified	2
4811	Telephone Communication	2
4830	Radio - T.V. Broadcasters	2
4911	Electric Services	8
4923	Natural Gas Tramsmis. - Distr.	1
4924	Natural Gas Distribution	4
4927		1
4931	Electric and Other Serv. Comb.	8
5140	Wholesale - Groceries and Related Products	1
5199	Wholesale - Nondurable Goods NEC	1
5661	Retail - Shoe Stores	1
6199	Finance - Services	1
6790	Miscellaneous Investing	1
7011	Hotels - Motels	2
7500	Service - Auto Repair and Service	1
7810	Service - Motion Picture Products	2
9997	Conglomerates	2
	Total	108

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