Accounting Data and Stock Returns Across
Business-Cycle Associated Valuation Change Periods

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(ABSTRACT)

This study examines intertemporal variation in the associations of accounting data with subsequent firm returns. A number of accounting research studies pool data indiscriminately across time and firms. Previous research has disclosed the nature and effects of cross-sectional dependencies in pooled data. On the other hand, intertemporal dependencies associated with real macroeconomic phenomena have not been widely researched.

The objective of this study was to provide evidence as to whether accounting data's associations with subsequent firm returns systematically vary across recession-associated and expansion-associated valuation change periods. Eighty-two accounting ratios were examined for evidence of systematic variation in association across business cycle-associated valuation events. Analyses are conducted, using both simple and multiple regression. Business cycle effects on the predictive accuracy of regression models were also examined.
The results indicate that for several accounting-based ratios, associations systematically vary across the business cycle. Business cycle events can thus confound the interpretation of results when studies use these accounting numbers and pool data across business cycle events.
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This dissertation is dedicated to my father, Clarence John Kane, and mother, Virginia Ruth Kane. Their faith in me, together with their conviction about the great value and opportunity of academics and education, have given me the strength, will and fortitude to persevere and achieve. In memory of them, therefore, I dedicate this work.
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CHAPTER 1
INTRODUCTION

1.1 MOTIVATION

In this century, economic history has been analyzed using two different paradigms (following Kuhn, 1970). The first views business phenomena as deriving from cyclical trends and forces. The second envisions business occurrences as collections of unique and random events (Thoreau, 1987). Financial accounting research has primarily been approached using the latter paradigm, in keeping with the general academic consensus of the post-war era. This approach has yielded many new insights, including the recognition that ext-ante expectations (i.e. market efficiency) can affect the predictive usefulness of financial accounting information (Ball and Brown, 1968).

Unfortunately acceptance of this paradigm has also propagated a wide schism between academic thought and financial accounting practice and application. In the world of business, of which financial accounting is a part, the notion of the classic business cycle is alive and well. Even a cursory examination of the business media, with the constant
assessments and predictions of impending recession and expansion, will confirm this. Investors, governments, government agencies and financial institutions regularly publish theories and notions of whether recession (or expansion) has or will occur.

Assuming that human behavior is rational, such a widespread recognition of discrete business cycle events in the business community should imply the existence of meaningful business cycle relationships. These relationships can be categorized as follows. First, it is intuitively plausible that firm managers may behave differently in recessions as compared to expansions. This in turn may affect future cash flows and ultimately, security returns. Accounting data may proxy for these behavioral effects. Second, if the business community predicates investment decisions on the basis of business cycle expectations, then the predictive decision usefulness of accounting data, hereafter referred to as PDU, may vary as a function of these conditioning processes. Finally, there may be important relationships between firm structure and business cycle events that have not been captured by previous event studies. Accounting data may proxy for these structural characteristics.

Most previous empirical studies have assumed that accounting associations with subsequent returns are stationary in time. Yet this assumption has not been examined extensively.
in the literature. In particular, accounting ratio associations with subsequent return may be affected by the business cycle. Non-stationarity in accounting associations may thus exist across recession and expansion events. If this is the case, then studies that have found significant associations between accounting data and subsequent returns may be interpreted, when they include data pooled across business cycle events, as capturing business cycle event sensitivity. This may at least partly account for any significant findings, as opposed to other explanations such as market inefficiency or the ability of accounting data to separate transitory and non-transitory components of earnings (For example Ou, 1989; and Ou and Penman, 1989a and 1989b). If accounting data are found to systematically vary across business cycle events in their association with subsequent returns, this would hamper the interpretability of results for studies that indiscriminately pool data across business cycle events. Business-cycle occurrences represent potential confounding events for these studies.

The present research is thus motivated to investigate the existence of latent business cycle associations with accounting data. To limit the scope of such an inquiry to manageable proportions, the question is explored only in the passive investment decision context (i.e., investors are assumed to be price takers seeking only price appreciation and

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dividend income). Further, investors are assumed to utilize a "buy and hold" investment strategy.

Because the passive investment decision context, as described above, involves predictive modeling, the study is also motivated to extend the literature concerning the PDU of accounting data. Are accounting models' PDU affected by the business cycle event they are estimated and applied upon? This latter question invokes several issues that have surfaced in previous research on the PDU of accounting data. These include the inherent weaknesses of a historical cost basis of valuation, the lack of recognition of significant intangibles, the rise of competing non-accounting sources of information (that may have rendered accounting data's information content redundant or obsolete), the distributional (and cross-sectional) weaknesses of accounting ratios, and the problems of untimely information release.¹

1.2 THE RESEARCH QUESTIONS

There are two primary research questions of concern in this study. They are described in subsections 1.2.2 and 1.2.3. Because the research questions center around the notion of market valuation change periods that are associated with

¹See the AICPA's issues paper (1988) on the changing significance of financial statements, as well as Rimmerman (1991) and Elliot and Jacobson (1991).
underlying business cycle events, a conceptual definition of these periods is presented first.

1.2.1 Definition of a Business-Cycle Associated Valuation Change Period (BVCP)

"Business-cycle associated Valuation Change Periods", hereafter referred to as "BVCPs", are periods of major systematic price revaluation that result from new information about unfolding major recessions or expansions. Accordingly, the BVCP is expected to occur immediately preceding or coincident with an underlying major recession or expansion.

BVCPs are further defined as "similar" if the same type of triggering event is associated with each BVCP. For example, if two BVCPs each precede, or are coincident with, a major recession, then the BVCPs are similar because the triggering events in both cases are of the same type. Conversely, if the triggering events are different, so that one BVCP is recession-associated and the other is expansion-associated, then the BVCPs are "dissimilar".²

² This is a very general definition of a BVCP. It is designed to introduce the concept. A full and formal definition can be found in section 3.2 of the "Theoretical Development" chapter.
1.2.2 The Association of Accounting Data to Abnormal Returns During BVCPs

The study begins by investigating the basic question of how accounting data are associated with cumulative abnormal firm returns during subsequent BVCPs. At issue is whether accounting associations with subsequent cumulative abnormal returns vary systematically across BVCP type. Subsequent cumulative abnormal return associations are examined for two reasons. First the investment decision an investor faces is predictive in nature. He/she must use current data to predict future returns. The PDU of accounting data is therefore a function of accounting data's association with subsequent BVCP returns. Second, the associations of accounting ratio data may vary in reaction to the BVCP event of interest. By measuring accounting ratio data at a point immediately previous to the event of interest, the possibility of associations being confounded by interaction with the business cycle event is minimized.

If the associations of accounting data with subsequent BVCP abnormal returns are stationary across business cycle events, then there should be no significant systematic

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3The precise meaning of "abnormal returns" is defined in section 3.3. As discussed in detail in that section, abnormal returns are used to detect parameter shifts across dissimilar BVCPs and to control for unique differences across BVCPs.
differences across similar and dissimilar BVCPs in cross sectional tests of the associations of accounting-based variables with subsequent BVCP abnormal returns. On the other hand, if there are exclusive latent business cycle relationships to which accounting data are sensitive, these associations should vary across dissimilar BVCPs but not similar BVCPs.

1.2.3 The Question of Accounting data’s Predictive Decision Usefulness Across Business Cycle Events

The second question of concern in this study is whether the PDU of accounting data is affected by business cycle events. Assume for the moment that accounting data associations with abnormal returns are not stationary across business cycle events. This may affect the PDU of accounting data in two ways. First, PDU is partly determined by the prediction accuracy of a given model. If the associations of accounting data with abnormal returns vary as a function of the operative business cycle, then models that use accounting data must be separately estimated in each business cycle in order to properly test the predictive accuracy of the resulting models. This is true even if investors all have exactly the same probability assessments about future expansion and recession. When researchers fit one model indiscriminantly across recession and expansion, they INTRODUCTION
implicitly assume stationarity. This assumption may not be valid.

Second, if investors form user-specific, heterogenous expectations of future business cycle events, then the PDU of a given accounting model may vary for each business cycle event on which investors condition on. This is because investors may form valuations that are no longer congruent with what is reflected in the current market price (which presumably reflects an aggregate consensus). Accounting data may serve to aid in this user-specific valuation process. The following subsections explore this notion of heterogenous beliefs further.

1.2.3.1 The Investment Decision Context

Visualize PDU from the individual investor's personal perspective, as opposed to an aggregate market definition. The investor's objective is to choose, based on the perceived value of future expected cash flows, a set of securities to buy and sell. This value is determined by invoking a personal assessment of future economic conditions. So the question of predictive usefulness can be framed in terms of how well accounting information helps the investor determine this perceived "value", given the veracity of the related user-specific expectations. This "personalized" view better accommodates the question of usefulness to the individual
investor and is consistent with professional concepts statements, as will be discussed. The individual investor's perspective may include a priori, user-specific probability estimates of the business cycle events known popularly as expansion and recession. These user-specific expectations, and cursive support for their existence, are now presented.

Many popular security return models are based on the assumption that investors have homogenous expectations, or at least behave as if this is the case. Perhaps the most popular example is the familiar Capital Asset Pricing Model (Sharpe, 1963). While this assumption is mathematically tractable, the notion of homogenous expectations is an abstraction that does not map well into real market conditions. Nevertheless, such an assumption is perhaps a reasonable approximation when aggregate market behavior is being modeled. Arbitrage mechanisms (together with arguments for the existence, at least among some market participants, of rational pricing expectations) may be invoked to support an homogenous expectation assumption because efficient markets should then behave as if expectations are homogenous. While this rationale may be acceptable for questions at the aggregate level of market behavior, a cursory examination of the media and other public business information sources suggests a very different individual decision context. Investors appear to form heterogenous expectations about future events. They may design
user-specific trading strategies that seek to maximize profits based on these expectations. In particular, investors may form heterogeneous expectations about business cycle events.

1.2.3.2 Heterogeneous Expectations of Business Cycle Events

As noted earlier, a great deal of public media attention is typically focused on the business cycle, and the direction of the economy. Diverse opinions concerning the state of the economy, including forecasts of recession and expansion, are made regularly in the popular business media such as PBS's Wall Street Week. Many security analysis services base earnings expectations on a belief about the future direction of the economy as a whole. For example, Value Line Investment Survey qualifies its earnings expectations with statements about expected future expansion and recession. Some news services provide security risk measures that are based on market direction. The Dow Jones News Retrieval Service, via MG Financial Services, provides an "up" and "down" beta for stocks listed on its database.

1.2.3.3 Predictive Decision Usefulness and Business Cycle Expectations

The Financial Accounting Standards Board (FASB) defines accounting data's decision usefulness along several dimensions in Concepts Statement No. 2 (SFAC 2). Accounting data's
decision usefulness is assessed from the individual user's perspective. Accounting data, according to SFAC 2, should be relevant, with "predictive value" to the user. It should be "capable of making a difference in a decision by helping users to form predictions about the outcomes of past, present and future events". Predictive value is thus defined within the context of specific event forecasts, according to SFAC 2.

Heterogenous expectations about the occurrence of events such as recession and expansion may affect accounting data's PDU. This possibility may be a contributing reason for SFAC 2's event-specific assessment criteria. If individual investors have heterogenous expectations of future expansion and recession events, and these expectations differ from the market consensus, then a security's market value (as reflected in its quoted price) may not reflect the perceived value of the security to the individual investor. This is because value, to the individual investor, may be associated with personally unique expectations. Accounting data may help the individual assess the valuation outcomes of personal expectations of future expansion and recession events. This may increase the PDU of accounting data. This kind of usefulness may vary, depending on whether return is being predicted for a recession or an expansion.
1.2.3.4 The Question of BVCPs and Predictive Decision Usefulness

In summary, the PDU of accounting data may be affected by business cycle events. The present research examines the question of whether this is the case for models developed with recession-associated and expansion-associated BVCP accounting and abnormal return data. If PDU is affected by BVCP type, then models estimated with recession-associated BVCP data will predict abnormal returns better in recession-associated BVCPs than in expansion-associated BVCPs. Similarly, the reverse should be true for models estimated with expansion-associated BVCP data. If PDU is not affected by business cycle events, then there should be no difference in predictive accuracy for models estimated with data from a specific BVCP type, irrespective of which type of BVCP was occurring in the prediction period.

1.3 PURPOSE OF THE STUDY

This study reported here was an analysis of the effect of business cycle phenomena on accounting data's associations with security returns. Two related areas of interest are explored. First, the study provides evidence as to whether the associations of accounting data with abnormal security returns are affected by business cycle events. Evidence is presented
as to the magnitude, direction and robustness of any association that is specific to BVCP type. Second, the study provides evidence as to whether the PDU of an accounting-based information system, as used in a multivariate linear model, is affected by business cycle events.

1.4 ORGANIZATION OF THE DISSERTATION

In this dissertation, the associations of accounting data to abnormal returns across BVCPs are reported as follows. In Chapter 2 the first part of the literature review is presented. Previous research is examined to determine if accounting associations with return are stationarity across both types of BVCPs (recession-associated and expansion-associated). Further, the extensive literature on PDU is broadly analyzed. The purpose is to determine if accounting data have been shown to have information content and predictive value, with respect to abnormal returns, in non-conditioned investment decision contexts. The CAPM model and the more recent multi-beta and arbitrage pricing theory models of risk are also discussed.

In Chapter 3, a theory of business cycle non-stationarity is presented, using CAPM (singular and multi-beta) pricing and

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4The review here is in the generalized context. Accordingly, no attempt is made to exhaustively review this voluminous literature.
assumptions. The theory demonstrates that accounting data's associations with abnormal return can vary across business cycle events.

Chapter 4 presents the second part of the literature review. This part focuses on methodological and data inclusion issues. The first section reviews previous research to determine the appropriate statistical model to use in return prediction when accounting data are employed as independent variables. A further section examines previous studies to determine what accounting data have been found to be significantly associated to security returns.

The design and methodology of the empirical portion of this research are described in Chapter 5. Chapter 5 includes operational definitions of BVCPs, the dependent variables, and a description of the accounting data set that is investigated. It also includes discussion of the testable hypotheses, the research design and a full description of the simple and multiple regression analyses.

Chapter 6 presents the empirical results. The analysis proceeded in two stages. In the first stage, an extensive simple regression analysis was conducted. The associations of accounting ratio variables (or transformations of these) to a standardized cumulative abnormal return metric (SAR) were estimated in simple linear regression models. Both pooled (across similar BVCPs) and unpooled (within individual BVCPs)
data were examined for each BVCP used in the study (excluding the holdout periods). Associations are examined to determine if they are specific to a given BVCP type. The robustness of these associations' direction and magnitude was also examined as a criterion for inclusion of accounting ratios into the second stage: the multiple regression analysis.

The multiple regression analysis consisted of two parts. In the first part, any significant simple regression results were retested in a multiple regression environment. Collinearity tests were first conducted and the variable set reduced, where necessary, to assure the interpretability of individual coefficient signs and values. Influence and residual diagnostic procedures were also used to determine cross-sectional regions where a general model might be misspecified. Residual dependencies that relate to industry effects were also investigated.

The second part of the multiple regression analysis began with a procedure to select "best" prediction models, based on accounting ratio data. The models were then estimated separately for each type of business cycle event by using pooled recession-associated and expansion-associated BVCP data. The models were then used to predict future BVCP size-adjusted, standardized abnormal returns (SARs) from holdout samples of each BVCP type. The prediction errors were tested to determine if average predictive accuracy was greatest when

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holdout BVCPs and BVCPs used in model estimation and variable selection were matched by BVCP type. If PDU increases, this would suggest that the PDU of accounting data is affected by BVCP type.

Chapter 7 presents the conclusions. Limitations of the study and suggestions for future research are also presented.
2.1 INTRODUCTION

The literature review for this study is presented in two parts. The first part, presented in this chapter, explores the key conceptual issues: stationarity of accounting data's associations with abnormal returns across business cycle events; and the predictive decision usefulness (PDU) of accounting data. The second and final part of the literature review, presented in Chapter 4, analyzes previous research related to the methodological issues of this study, including variable and model selection.

In this chapter, previous studies are first examined for evidence of the stationarity of accounting data's association with abnormal stock returns across the two business cycle related market events: recession-associated and expansion-associated BVCPs. Following this, some of the voluminous research on accounting data's information content and predictive usefulness is reviewed.
2.2 Stationarity of Accounting Data Associations Across Business Cycle Events

The previous evidence on stationarity of accounting data associations across business cycle events is classified, for purposes of this review, as being "direct" and "indirect". Direct evidence consists of those studies that used a business cycle-related definition of market direction to detect the existence of shifts in association. Indirect evidence consists of those studies that used non-business cycle related definitions of market direction to detect non-stationarity. Studies that used "direct" research methods are presented in section 2.2.2; those that used indirect market definitions are presented in section 2.2.3.

Several of the studies presented in this section sought to detect nonstationarity in the Capital Asset Pricing Model's (CAPM) beta. These are included because accounting ratios have been shown to be associated with beta (Beaver, Kettler and Scholes, 1970). The theoretical development that follows in Chapter 3 also utilizes this linkage. For this reason, the CAPM and the more recent multi-beta and multi-factor extensions are first discussed. The theoretic and empirical evidence for the association of beta (and related multiple betas and factors) with accounting data are also briefly
presented. This association is further developed in Chapter 3.

2.2.1 CAPM and Related Asset Pricing Theories

2.2.1.1 The Capital Asset Pricing Model (CAPM)

The Capital Asset Pricing Model, hereafter referred to as CAPM, postulates the following ex-ante return generation model:

\[ E(R_i) = R_f + \beta_i[E(R_m) - R_f], \]  \hspace{1cm} (2.1)

where \( R_i \) is the return on security \( i \), \( R_m \) is the return on a market portfolio of all assets, \( R_f \) is the risk free rate of interest, here assumed constant, \( E \) is the expectation operator (under normal probabilistic assumptions), and \( \beta_i \) is the systematic sensitivity of security \( i \). Because both \( R_i \) and \( R_m \) are random variables, beta is:

\[ \beta_i = \text{Cov} (R_i, R_m) / \sigma_m^2, \]  \hspace{1cm} (2.2)

where \( R_i \) and \( R_m \) are as defined previously and \( \sigma_m^2 \) is the variance of the market portfolio. An empirical model, related to equation (2.2), and stated ex-post, is popularly known as the market model:
\[ R_i = \alpha + \beta_i R_m + \mu_i, \]  
(2.3)

where all terms are as previously defined and \( \mu_i \) is a disturbance term assumed to be an independent and identically distributed random variable from a normal distribution with a mean of 0 and variance of \( \sigma^2 \). Equations (2.1) and (2.3) both make similar statements: the only factor, or variable, that is systematically priced into security returns is a security's covariance with the market portfolio. Other risk associated with owning a security can be diversified away by an investor who holds a large and well diversified set of securities.

Accordingly, under CAPM, because no other factor is priced into security returns, all other "factors" do not affect ex-ante return generation and are irrelevant. With the assumptions of quadratic utility functions and homogenous preferences, \( \beta_i \) becomes the appropriate measure of security risk and the appropriate portfolio for all investors to hold becomes the market portfolio itself.5 Investors then adjust weights on the holdings of only two "funds": a mean-variance efficient market portfolio and either a risk-free asset, if

5The same results can be obtained with the assumption of bivariate normality. In this case, quadratic utility functions are no longer necessary to prove equation (2). Note also the conceptual equivalence of risk and return when risk aversion is assumed. Because investors prefer no risk, they require a "premium", built into the return generation model of equation (2), \( R_m\cdot R_i \), to hold risky assets.
one exists, or a zero-beta portfolio in the sense of the Black model (Black, 1972). This two-fund separation result (Tobin, 1958; Markowitz, 1958) was the direct result of restrictions on investor preferences and made CAPM theoretically tractable. Further, equation (2.1) can easily be converted to ex-post terms by the addition of a disturbance term with mean zero, as with equation (2.3).

The simple linear relation of equations (2.1) and (2.3) is also quite intuitive. Indeed, long before CAPM, the investment community was well aware of the need for diversification (and thus the old adage not to "put all your eggs in one basket"). Further, CAPM's theoretic grounding in the assumption of mean-variance efficiency fits quite well with currently accepted notions of a rational risk averse investor constantly seeking, as a sole objective, to optimize

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6Black, Jensen and Scholes (1972) find evidence to support a two-factor CAPM, where the second factor is a zero-beta portfolio.

7Numerous other restrictions were also required under the mean variance theoretic approach. These included fully divisible assets; perfectly competitive markets; unlimited borrowing and lending possible at the risk free rate; no transaction costs; frictionless markets; maximizing investors (with respect to wealth) with homogenous expectations. The CAPM was also a one period model, though later extensions (such as Merton, 1973) extended CAPM to a multi-period framework and relaxed many of the above assumptions (For example, see Black, 1972; Brennan, 1971; Mayers, 1973; Breeden, 1979).

8The further assumption of homogenous expectations of expected returns and variances, by all investors, is needed to map the ex-ante return generation model to its ex-post relative.

LITERATURE REVIEW I
wealth in the mathematically tractable sense, thereby optimizing utility.

An extensive literature has attempted to test CAPM’s theoretical implications by substituting market proxies for the market portfolio.⁹ Roll’s critique however (Roll, 1977) demonstrates the futility of such tests. Roll demonstrates that unless the true market portfolio can be identified no test of CAPM is possible. Tests will only determine if the index proxy for the market portfolio that is used is mean-variance efficient within the sample. These empirical tests can say nothing as to whether the true market portfolio is itself mean-variance efficient, even if the proxy chosen turns out to be so. Therefore, tests of the CAPM are impossible because they require measurement of an unobservable (the market portfolio). This strong result leads to the fundamental question of whether an unfalsifiable statement can be considered a legitimate theory.⁹⁰

CAPM has also been called into question by amalgomous findings that suggest the presence of other factors.¹¹ Of course, the issue of whether CAPM is a perfect description of

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⁹Important contributions to this effort include Fama and MacBeth (1970) and Black, Jensen, and Scholes (1972).


¹¹See, for example, Ball (1978), Basu (1977), Reingeinum (1981), and Keim (1983).
the world, or even whether it is a legitimate theory, can be set aside by the following simple empirical argument. When the purpose of a model is to forecast future returns, the only reasonable criterion for that model is how well it predicts. Does it tell us something about return generation that we did not know previously (Fama, 1991)? Unfortunately, in the case of CAPM and the associated beta estimate, the answer to these questions appears to be "no". Most beta proxies that have been used appear to have no real explanatory power with respect to security returns. Lakonishok and Shapiro (1986) found that beta does not significantly explain cross-sectional security returns when beta estimates are obtained by forming portfolios based on size, total risk, and systematic risk. The result holds for individually estimated betas as well. Fama and French (1992) also found that the relation between the common $\beta$, parameter estimate and average return is flat, after controlling for firm size. Additionally, there has also been a long standing debate over the intertemporal stability of beta.\footnote{See Fama and MacBeth (1971), Sharpe and Cooper (1972), Downes and Dyckman (1973), Levy (1971, 1972 & 1974), Meyers (1973), Baesel (1974), Blume (1971 & 1975), Elgers, Haltiner, and Hawthorne (1979), Rosenfeldt, Griepentrog and Pflaum (1978), Levitz (1974), Fouse, Jahnke and Rosenberg (1974), Altman, Jacquillat and Levasseur (1974), Wallace (1980), and Modani, Cooley and Roenfeldt (1983).} The summary finding of this research has been that
individual betas are not very stable across time for individual securities.

One finding of interest in the Lakonishok and Shapiro study concerns beta associations in up and down markets (to be fully discussed in Section IV). Their study found that beta, firm size, and standard deviations of residuals in the market model regression all have significant explanatory power in up and down markets. The definition they use for "up" and "down" markets, however, is not clarified in the paper.

2.2.1.2 Arbitrage Pricing Theory

As disenchantment grew with the CAPM related models, other theories were developed throughout the 1970s to explain the ex-ante process that generated security returns. One of the most notable was Arbitrage Pricing Theory, herein referred to as APT, as developed by Ross (1976; 1977). The theory’s major attraction is that it is developed from a simple arbitrage argument (as opposed to a mean-variance efficient framework). As a result it enjoys the significant advantage of requiring much weaker theoretic assumptions than the CAPM. Without assumptions on utility functions, probability distributions, or mean-variance efficiency, APT demonstrates that the basic result of the CAPM (that diversifiable risk is not priced) holds in a far more plausible and general context. The theory also extends the notion of a single market factor
to many factors that drive security returns.\textsuperscript{13} For these reasons, it is presented briefly here (Following Ross, 1977).

First, an arbitrage portfolio is formed such that net investment is zero. If weights on the given assets are described by vector \( w \) then

\[
wr = 0,
\]

(2.4)

where \( r \) is the unit vector. The ex-post return on the arbitrage portfolio can be written as

\[
R = w'\bar{L} + w'\bar{\beta} + w'^{\varepsilon},
\]

(2.5)

where \( \bar{L} \) is the expected mean return vector of a set of assets, \( \bar{\beta} \) is a vector of beta coefficients, \( \bar{\alpha} \) is the risk premium for holding systematic risk, and \( \varepsilon \) is a vector of random errors. Note that no distributional assumptions are placed on \( \varepsilon \).

Second, an arbitrage portfolio is chosen such that all systematic risk is eliminated. Therefore:

\textsuperscript{13} Multi-factor models, based on CAPM, were also being developed in the 1970s (Rosenburg and Guy, 1976; Rosenberg and McKibben, 1973; Sharpe, 1977). Further, the notion of multiple factors influencing security returns is not at all new. For example King (1966) and Cohen and Pogue (1967) introduced early multiple factor models. Despite these related multi-factor efforts, the simplicity and intuitive appeal of the single factor CAPM model inspired a strong paradigm that was prevalent at the time of the emergence of APT. Accordingly, APT seems to have been a major contributor in the emergence of the newer multi-factor paradigm.
\[ w' \beta = 0, \]  

where all terms are as previously defined. By the law of large numbers, the error term \((w' \epsilon)\) is eliminated.\(^4\) Now equation (2.5) becomes

\[ R = w' L. \]  

(2.7)

To avoid riskless profits \(w' L\) must equal 0. If \(w\) is orthogonal to \(\mathbf{r}\) and \(\beta\), then \(w\) must be orthogonal to \(L\) also; therefore, \(L\) must be a linear combination of \(\mathbf{r}\) and \(\beta\). The original one factor model is thus derived by the simple arbitrage argument above:

\[ L = L_0 + \alpha \beta, \]  

(2.8)

\(\text{\footnotesize{\textsuperscript{4}}It turns out this is not quite correct. As the number of assets increases, wealth may also. This may increase risk aversion for some economic agents, thus canceling out the diversification effect of large numbers of different assets. Further, because there are no distributional assumptions, variance may not be bounded so that the error term cannot be diversified away. Ross (1976) develops a rigorous argument for APT by adding the following assumptions to the theory: lower boundedness because of limited liability; type B agents that are "non-negligible and believe in the APT return generation model; homogeneity of expectations; all agents are risk averse; disequilibria that only involve assets with excess demand; upper boundedness of expectations. The added assumptions, while not trivial, are still far weaker than those required for CAPM.}}\)

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where all terms are as previously defined and $L_0$ is the return on a zero beta portfolio of assets. It turns out that $\alpha$ can be interpreted as the familiar market risk premium (expected return on the market portfolio less expected return on a zero beta portfolio). Thus, APT can be reduced to the original CAPM. On the other hand, because the arbitrage argument is quite general, $\alpha$ can represent any systematic risk premium (thus removing the theoretic dependency on the market portfolio) and can be generalized to a $k$ factor model:

$$R_i = L_0 + \beta_{i1} \delta_1 + \beta_{i2} \delta_2 + \ldots + \beta_{ik} \delta_k + \epsilon_i,$$  

(2.9)

where $\delta_j$, with $j=1\ldots k$, is the $k$th risk premium ($\alpha$ in the derivation above) on an arbitrage portfolio selected so that all other $k-1$ factor betas are equal to 0 and $w'B_k$ equals 1.

As mentioned, APT is derived with much weaker assumptions than the original CAPM. As such, it appears to avoid much of Roll's criticism and is more general. On the other hand, APT has been criticized for being devoid of economic meaning. Note that equation (2.9) makes the general statement that there can be $k$ common factors that generate security returns. Yet no statement is made at all concerning what those factors might be. In this sense, APT is actually less useful than CAPM in
prediction applications, where at least one factor (the market portfolio) is specified.

Tests of the APT model generally employ principal components analysis, following Roll and Ross (1980) and Gehr (1975). In general, three to four common factors are identified, although their identity and time-invariance are indeterminable, either theoretically or empirically. This constitutes a major flaw in the APT framework. Further, Shanken (1982) shows that APT, like CAPM, is non-testable. The number of factors can be shown to vary, within sample, by creating linear combinations of underlying assets. Dhrymes, Friend and Gultekin (1984) show that the number of factors detected by factor analysis increases with the number of firms that are analyzed. On the other hand, Brown (1989) shows that factor analytic results will weight a single factor as most important when in fact there may be several equally important factors. Shanken (1982) shows that APT is untestable because the assumption of finite variance is required. All sample data

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This technique requires the assumption of multi-variate normality, thus weakening, at the point of testing, the differences between CAPM and APT in terms of required assumptions.

Dybvig and Ross (1985) criticize Shanken's transformation finding, citing two asset transformations are "degenerate". They are not generalizable to the large n assets case because idiosyncratic variances increase exponentially under the transformation procedure.
will exhibit this property in the variance estimates, even if
the assumption does not hold.

In summary, neither the single factor CAPM nor the APT
return generation model has demonstrated strong and robust
predictive usefulness. Single factor CAPM beta estimates have
been shown to have little, if any, explanatory power with
respect to average security returns. The APT model, while
allowing for k factors, gives no information as to what
underlying economic factors influence security returns. This
raises the question of what macroeconomic factors, that are
non-accounting based (as measured), may influence and predict
security returns? This issue leads to the last set of non-
accounting information studies to be considered here: Research
that went beyond market-derived variance-covariance
relationships to postulate various exogenous multiple economic
factors as the ultimate source of systematic risk. These types
of models, generally referred to as "multiple beta CAPMs", are
the focus of the following sub-section.17

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17The term is used here broadly because multi-beta CAPM models
would, by definition, include only models derived or extended from
CAPM. Other models, such as equation (12), are close relatives to
the multi-factor CAPM notion and are therefore included as part of
this class.
2.2.1.3 Multi-Beta and Real Economic Factor Models

As mentioned, Sharpe (1977), Rosenberg and Guy (1976) and Rosenberg and McKibben (1973) have developed multi-beta interpretations of the CAPM. These models decompose the market return into a linear combination of several exogenous economic "factors".\textsuperscript{18} One model presented below follows Rosenberg and McKibben (1973).\textsuperscript{19} Assume that beta is linearly related to several "real" economic determinants. Then

$$\beta_{it} = \sum_{n=1}^{N} W_{itn} b_{in},$$ \hspace{1cm} (2.10)

where $\beta_{it}$ is the beta coefficient in equation (2.1) for firm $i$ at time $t$.\textsuperscript{20} The variable $W_{itn}$ is the $n$th real determinant with summation over $N$ real determinants. The constant $b_{in}$ is the firm $i$'s linear coefficient associated with the $n$th real

\textsuperscript{18}"Exogenous" is used loosely here. In the strictest sense, very few variables can be truly exogenous to any system. The stock market, for example, may influence macroeconomic inflation, business activity and other "exogenous" events, as well as be influenced by them. The notion of two independent systems is simply a useful abstraction.

\textsuperscript{19}Myers (1977) presents a reduced version of this presentation.

\textsuperscript{20}The $t$ subscript is added to permit time-variance of $\beta$ in response to changes in economic factors.

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determinant. Substituting into equation (2.1) and subtracting the risk-free rate from both sides yields

\[ E(R_{it}) - R_{ft} = \sum_{n=1}^{N} w_{int} b_{in} [E(R_{mt}) - R_{ft}], \]  

(2.11)

where all terms are as previously defined. Equation (2.11) states that the independent variables are the product of the ex-ante market risk premium and the hypothesized economic determinants of beta.

An economic state model that is related to equation (2.11) directly associates economic state proxy variables to security returns using the multivariate model used in Chen, Roll, and Ross (1986), herein referred to as "CRR". This model, in ex-post terms, is as follows:

\[ R_{it} = a + \sum_{n=1}^{N} w_{nt} b_{in} + \epsilon_{it}, \]  

(2.12)

where all terms are as previously defined and \( \epsilon \) is a random variable assumed to be distributed iid\( \sim N(0, \sigma^2) \).

A third k-factor CAPM model follows Kim and Wu (1987), herein referred to as "KW". This model is very similar to APT
above, except that the factors are generated by economic data and utilized in an extended CAPM derivation similar to equation (2.11) above. From equation (2.10), the market return can be written as:

\[ R_m = I_0 + \beta_{m1}\delta_1 + \beta_{m2}\delta_2 + \ldots + \beta_{mk}\delta_k + \epsilon_m, \]  \hspace{1cm} (2.13)

where

\[ R_m = \Sigma_i w_i R_i \], with \( w_i \) being the proportionate value of security \( i \) to the value of all of the securities at the beginning of the period, and

\[ \beta_j = \Sigma_i w_i \beta_{ji} \] and \( E(R_m) = \Sigma_i w_i E(R_i) \) for \( j = [1 \ldots k] \) and

\[ \epsilon_m = \Sigma_i w_i \epsilon_i. \]

The substitution of equation (2.13) and equation (2.10) into the CAPM model, equations (2.1) and (2.2), with simplification and the elimination of idiosyncratic error terms (these are assumed to have mean zero with large \( n \)) yields:

\[ E(R_i) = R_f + f_1\beta_{i1} + f_2\beta_{i2} + \ldots + f_k\beta_{ki}, \]  \hspace{1cm} (2.14)

where
\[ f_j = \left( \frac{[E(R_m) - R_f]}{\sigma^2} \right) \text{Var}(\delta_j) (\Sigma_i w_i \beta_{ij}) \text{ for } j=[1, \ldots, k]. \quad \] \text{21}

KW (1987) utilize equation (2.14) by submitting various economic proxies to principal components analysis in an effort to find underlying latent factors. Factor scores are then used as variables in the regression described by equation (2.14). In this sense, this methodology represents a kind of empirical connection between the CAPM and APT theories. Factors are theorized and generated from real macroeconomic series data using factor analytic techniques. The factors, once obtained, are then used in an extended CAPM regression model.

2.2.1.4 Systematic Risk and Accounting Data

All three major pricing theories (CAPM, APT and multi-beta) describe expected returns, \( E(R_i) \), for a given security \( i \). Returns, \( R_k \), at time \( t \) can be described as:

\[ R_k = (P_k - P_{k-1} + D_k) / P_{k-1}, \] \text{ (2.15)}

where \( P_k \) and \( P_{k-1} \) are the prices of the \( i \)th security (or the aggregate market value of the market portfolio in the case of

\[ ^{21}\text{For purposes of this computation, } L_0 \text{ in equation (2.13) is interpreted as equivalent to the risk-free rate (} R_f \text{).} \]

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\( R_n \), at time \( t \) and \( t-1 \) respectively. \( D_n \) is the \( i \)th security's dividend at time \( t \). The prices of a firm's securities (and the market portfolio) in equation (2.15) may be viewed, using the notion of present value, as the expected sum of all future cash flows discounted back by some required rate of return.

If accounting data proxy for the systematic sensitivity of a firm's expected future cash flows, then accounting data should proxy for beta in the CAPM model. This can be seen by substituting a cash flow definition of returns into equation (2.1). Beta then becomes a link between the expected future cash flows of the market and the firm. If accounting ratios could proxy for aspects of this cash flow function, then correlation between accounting ratios and beta would be expected. This notion of accounting data as proxy for systematic sensitivity can also easily be extended to the more recent APT and multi-beta theories described above. Beaver, Kettler and Moss (1970) used rank correlation coefficients to examine the empirical relationship between beta estimates and various accounting-based variables (including current ratio, leverage, dividend payout, log of the five year change in net book assets, an earnings beta and the standard deviation of earnings). Beaver, Kettler and Moss found evidence of this association. The theoretical development of Chapter 3
discusses more formally the association of accounting data and the CAPM beta.

2.2.2 Direct Evidence of Nonstationarity Across Business Cycle Events

Gooding and O'Malley (1977) tested for the stationarity of the Capital Asset Pricing Model (CAPM) beta across bull and bear markets. They found that betas are not stationary and appear to be affected by market direction. Gooding and O'Malley used market "phases" to define windows for "bull" and "bear" markets (they defined two long term phases for each). These "phases" appear to have been determined by graphic analysis of overall long term stock market trends. Therefore, the market phase definition was not explicitly linked to underlying real business cycle phenomena. While Gooding and O'Malley did not detail their methodology for deriving these market phases, the event windows they chose for these "phases" do correspond closely to several BVCPs that are used in this study. The assigned phase type (bull or bear) is also consistent with the BVCP types found in this study. Finding that the CAPM beta was not stationary and varied across bull and bear market "phases" is consistent with the notion that accounting data associations vary across BVCP type.

Krueger and Johnson (1990) found that the well documented firm size, earnings to price, and Valueline Timeliness
rankings anomalies vary across the business cycle. Their methodology uses the National Bureau of Economic Research (NBER) definitions of recession and expansion business cycle events. Krueger and Johnson made no additional adjustments to the NBER definitions in defining the period investors discounted these business cycle events. Accordingly, they implicitly assumed that investors discounted them as they happened. Because MMVCPs are defined by beginning with the NBER designations, the event periods used by Kreuger and Johnson, while not corresponding exactly, are nevertheless closely correlated with the event periods used in this study. The Kreuger and Johnson study analyzed the association of excess returns to the anomalies mentioned earlier by making quarterly observations and assigning these observations to "recession" and "expansion" groupings according to the NBER definitions. The anomalies' main and interactive effects were significant only in NBER expansions. Observations occurring in NBER recessions showed no significant associations between anomalies and excess returns. These results held for both portfolio and linear regression tests.

In addition to the few studies above that have directly analyzed business cycle associations, other research has

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Valueline Timeliness rankings are a quintile ranking system that uses, as a ranking criterion, values from a proprietary formula that weights and measures the "momentum" of changes in earnings and price.
looked at business cycle related phenomena that may affect accounting associations. Fama and French (1988) found that commodity metals pricing has a strong "business cycle component". Using a "theory of storage", Fama and French predict that differences in inventory levels will cause variations in spot price changes associated with a given increase in demand. As a result, there should be greater spot price variability around business cycle peaks (where inventories are lower because of positive demand shocks). Fama and French found evidence to support these predictions. Although Fama and French relate business cycle behavior to inventory at the aggregate level, firm-specific inventory levels may affect the degree to which a firm is susceptible to these spot price changes in variability. Accordingly, inventory measures, as well as accounting ratios that reflect costs of goods sold, would be expected to have associations with abnormal returns that vary with business cycle peaks.

Choe, Masulis and Nanda (1990) found evidence that larger numbers of firms issue common stock during expansionary phases of the business cycle. Changes in "adverse selection cost" are theorized to alter financing preferences in favor of equity. Accordingly, accounting ratio associations that are related to financing activity, such as long term debt repayment, and ratios that use equity as a deflator would be expected to vary with business cycle events. Choe, Masulis, and Nanda also use
the NBER recession and expansion definition. This, as mentioned earlier, is basically consistent with the event periods used in this study.

In summary, the extant evidence suggests that accounting data's association with abnormal return varies across BVCP type. The evidence is limited, however, to a fairly small group of studies that use direct business cycle definitions. Further, a recent study suggests that most of the return variations associated with business condition changes are a function of changes in the risk premium as opposed to changes in the firm specific beta (Ferson and Harvey, 1991).\(^{23}\) Return changes therefore may not be the result of beta shifts in equation (2.1). If this result applies generally, then systematic return changes across BVCPs should not be firm-specific and abnormal return associations with accounting data should not vary across recession-associated and expansion-associated BVCP types.

2.2.3 Indirect Evidence of Nonstationarity Across Business Cycle Events

A number of papers have looked at changes in beta in locally defined "up" and "down" markets. These studies have typically used short-term, non-cyclical definitions of market

\(^{23}\)This study also implicitly assumed stationarity across business cycle events.

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direction. In reviewing this indirect research, indirect definitions of "bull" and "bear" markets are compared and contrasted to the notion of a recession-associated and expansion-associated BVCP.

The first research on beta shifts across bull and bear markets is the seminal study by Fabozzi and Francis (1977). Examining security risk, and using a multivariate model that computed beta for up and down markets, Fabozzi and Francis found no evidence to support an hypothesis that security risk is affected by market direction. Kim and Zumwalt (1979) analyzed the variance characteristics of market risk in up and down markets. They found that most stocks showed no difference in up and down beta values. Eleven percent of their sample did have significantly different betas in up and down markets, however. Chen (1982) reexamined the conclusions of Kim and Zumwalt by controlling for multi-collinearity and heteroscedasticity in the beta estimation model. His results support Kim and Zumwalt's earlier findings.

Fabozzi and Francis (1977) employed three definitions of bull and bear markets. In two of these definitions returns were classified as "bull" or "bear" on a monthly basis. In one definition, if the \( R_m \) proxy was negative (positive) for a given month, the returns were classed as "bear" ("bull"). In a second definition, market proxy returns had to be
"substantial" in a given direction. "Substantial" was defined as more than half a standard deviation from the average of monthly market proxy returns over the period studied (1966-1971). Kim and Zumwalt (1979) and Chen (1982) also used the monthly classification procedure described in Fabozzi and Francis, although different benchmark cutoff levels were sometimes used.\textsuperscript{24} The monthly classification procedure described above is a short-window procedure that has questionable utility for detecting long-term associations.\textsuperscript{25} Because the definition is based on monthly returns, no inter-monthly trend would be detected. If the recession or expansion is discounted across a longer event window than one month, this definition may inappropriately classify a return as "bull" when it occurs during a "bear" trend.

Another major problem with the arbitrary and mechanistic definitions used by these studies is that they are devoid of economic content. While the definitions are based on market-based return direction, no link is made to any fundamental economic event that may be driving the market proxy return. Fabozzi and Francis (1977) do give some slight attention to

\textsuperscript{24}These included the three month treasury bill rate and the average of various monthly market return proxies.

\textsuperscript{25}A financial analyst's concept of bull and bear markets is often that of a long-window state or event. For example, some technical analysts use the notion of bull and bear trends over different window lengths (on the financial news network, FNN, they are described as long-term, intermediate, and short-term).
this concern by using, as a third definition of bull and bear markets, a "popular investments textbook" to class "bull" and "bear" periods. Nevertheless, no mention is made concerning what basis the textbook used for determining these classifications. A problem related to this lack of economic meaning is the fact that sample periods used by these studies are not selected to specifically capture the discounting effects of underlying macroeconomic recessions and expansions that may have been occurring. Taken together, these comments simply reflect that the studies were not specifically designed to capture the effects of long term bull and bear market trends associated with major expansion and recession.

While Fabozzi and Francis (1977), Kim and Zumwalt (1979) and Chen (1982) generally found that market direction did not affect systematic risk or expected returns, one other indirect study did find significant return effects associated with market direction.

Wiggins (1992) examined the differences between "up" and "down" betas for various portfolios ranked by size. He found that large firms have significantly smaller up betas than down betas. Smaller firms have significantly larger up betas than down betas. Wiggins (1992) also looked at directional betas for "loser" and "winner" portfolios formed on the basis of the previous five years' results. Wiggins found that loser portfolios have higher up betas than down betas in the
following period whereas winner portfolios exhibit just the opposite relationship. The Wiggens study appears to have followed Fabozzi and Francis' bull and bear market definition, although this is not explicitly stated in the study.

In conclusion, the results of previous research using indirect definitions of "up" and "down" market direction are mixed. Results are ambiguous concerning whether market direction is important when short-term event windows are used to define up and down markets. Generally, most of the research is not able to detect significant shifts in association. None of this "indirect" research looked at the association of accounting data with abnormal return across indirectly defined up and down markets.

2.3 THE INFORMATION CONTENT AND PREDICTIVE VALUE OF ACCOUNTING DATA

2.3.1 The Information Content of Accounting data

This section examines some of the voluminous research concerning accounting data's information content and predictive value. The most basic question to begin with is whether previous studies have shown that accounting data have any information content that may affect investment decisions. The seminal study that addressed this question was Ball and
Brown (1968). Ball and Brown predicted that unexpected increases in accounting-based earnings are associated with positive abnormal rates of returns on stock investments. Their tests of cumulative abnormal return indicate there is a positive association between earnings and return, but most of the association occurs prior to the earnings announcement. They conclude that accounting earnings are not a very timely source of information. Brown (1970) essentially replicated the Ball and Brown design using Australian firms and, together with other studies, confirmed the Ball and Brown results.

Foster (1977) conducted a seminal quarterly earnings study, using daily returns and a slightly different methodology. Using the widely adopted cumulative abnormal return index, he found an association between abnormal return and unexpected quarterly earnings. Several related studies have analyzed magnitudes of association of unexpected earnings and abnormal returns (e.g., Beaver, Clarke and Wright, 1979 and Beaver, Lambert and Morse, 1980), as well as abnormal return variances around earnings announcements (Beaver, 1968a). Abnormal returns have also been studied for over the counter securities (Grant, 1980). The conclusion of this stream of research is that accounting data, in the form of earnings, have information content. This content is largely discounted by the time of public announcement. Therefore, the
predictive usefulness of accounting data in an investment decision context is not well supported.

Note that the research described above studied abnormal returns, which are theorized in the Capital Asset Pricing Model (CAPM) to be uncompensated in security returns, because they represent a risk that investors can diversify away. Accordingly, while they may exist for short periods, these abnormal returns are unpredictable, at least in the semi-strong efficient market form, and would be expected to sum to zero over a long holding horizon. Ball and Kothari (1991) found that abnormal returns associated with earnings announcements have a minimal impact on beta, when beta is permitted to vary across earnings event windows. This implies that earnings information generates primarily diversifiable risk.

Easton, Harris and Ohlson (1989) conducted a study of the association of accounting earnings and return over longer event windows. They concluded that earnings could explain a large portion of security return over long holding periods ($r^2 = .63$ over ten years). Again, however, this association must be shown to be predictive ex-ante in order for investors to realize decision-usefulness from the accounting data's association.
2.3.2 The Predictive Content of Accounting Data

Given that accounting earnings have information content, have previous studies been able to show that other accounting data also have information content? Further, can the information content in accounting data be used for predicting firm risk and return? As discussed earlier, an early study that addresses this question was Beaver, Kettler and Scholes (1969). This study looked at the association of accounting variables with a market based measure of risk (beta). Using correlation analysis of two subperiods, they found that several accounting variables are associated with beta, but that association is not very robust across time. Therefore the predictive value of these variables is ambiguous.

A related area that utilizes the predictive content of accounting variables is the literature on bankruptcy prediction. Beaver (1966, 1968) found that accounting-number based ratios are associated with corporate failure up to five years prior to the event. Later, Altman (1968) pursued the same question using multiple regressions to predict failure. These studies, and many others since, have generally concluded that accounting data can be useful in predicting future failure, at least up to three years prior to the event.

More recent research on the predictive content of accounting data has challenged the question of market efficiency. Ou and Penman (1989a) conducted a study based on
the ideas of fundamental analysis. They used LOGISTIC multiple regression of accounting data to develop a trading rule. The rule is based on the capacity of historic accounting data to predict the detrended direction of earnings one year ahead. This rule was used to choose portfolios of securities in which long and short positions were taken in stocks. The portfolios were selected such that net investment was zero. Assuming risk was the same for both long and short portfolios, the net return should have been zero if accounting data were fully discounted in prices. Ou and Penman were able to earn a significant return over windows of more than two years, suggesting that the information content of accounting data is not fully discounted into prices, and therefore has predictive usefulness. In a related study, Bernard and Thomas (1989) found a delayed price response to previously reported earnings in later quarterly announcements. Hand (1990) found a reaction to stock swap earnings effects at the time of the quarterly earnings announcement.26 These gains were previously unrealized capital gains, which had been reported in earlier announcements. The reaction suggests that markets may not be as efficient as once believed.

26Ball and Kothari (1991) challenge this result, based on the correlation of Hand's proxy with size. See also Hand's reply (Hand, 1991).
Arrow (1982) argues that stock market trading may not reflect rational behavior. Shiller (1981) shows that stock price volatility exceeds that which can be reasonably explained by dividend changes. DeBondt and Thaler (1985) present evidence of stock price overreaction to dramatic news events. West (1988) analyzed possible causes for this phenomenon, including small-sample bias, rational bubbles and fads. He concludes that there is little direct evidence to support a fads theory, and that small-sample bias and bubbles do not adequately explain stock price volatility. Campbell and Shiller (1988) found that a long moving average of real earnings (deflated by current stock price) is a powerful predictor of return (particularly when return is measured over several years).

In summary, these studies open the possibility that historical-cost based accounting information may have predictive information content.

2.3.3 The Stability of Return and Risk

As mentioned earlier, market based risk (beta) has been shown to be unstable when computed for individual securities. If risk and associated return are intertemporally unstable, then the process that generates security returns may not be stable across time. This would limit the predictive decision usefulness of all information in an investment context.
Numerous studies have attempted to explain beta instability and improve estimation using past trends (Blume, 1975), bayesian estimation (Vasicek, 1973; Chen, 1981; and Klemkosky and Martin, 1975), stochastic theory (Fabozzi & Francis, 1978; and Chen, 1981), the modeling of variance and covariance changes across time,\(^\text{27}\) and alternative regression techniques (Cornell, Kimball, and Dietrick, 1978). Additionally, multiple factor models have been developed to explain security return (for example, see King, 1966; Ross, 1976; and Kim and Wu, 1987). While these approaches have improved on earlier results, the question of beta instability appears to remain unresolved.

On the return side, time series studies have analyzed and compared the return and earnings generation processes across time. Beaver (1970), Ball and Watts (1972) and Foster (1977) conducted a few of the early studies that pursued this line of investigation. These studies generally found some differences in the two time series. For example, Beaver (1970) found that accounting rates of return follow a similar time series pattern (mean reverting) as returns, but this pattern occurs over a much longer time period. More recent studies have found significant differences in the time series of returns,

\(^{27}\) See for example Engle’s seminal paper (Engle, 1982) and Bollerslev, Chou and Kroner’s summary paper (1990) on autoregressive conditional heteroskedasticity models (ARCH).
depending on the time horizons involved (Fama & French, 1988; Conrad and Kaul, 1988 & 1989). These later studies indicate that short term return shocks may rapidly decay, while longer term return horizons show a negative autocorrelation in return. Fama and French (1988) hypothesize and show evidence of a U-shaped curve to this autocorrelation, that peaks at a horizon of about four years. Relatively, Summers (1988) shows that long and persistent pricing errors may not be discernable using return data and present statistical tests.

In summary, the stability and concordance of accounting data with return and associated risk seem to remain open questions. There are indications from past research that accounting data have some stable predictive information content, but the extent and nature of this content is still the subject of ongoing investigation.

2.4 CONCLUSION

This literature review has addressed the key conceptual issues involved in this research. These issues include the stationarity of the association of accounting data with subsequent returns across BVCPs, the conceptual definition of recession-associated and expansion-associated BVCPs, and the information content and predictive value of accounting data.

The evidence from previous research, both direct and indirect, seems to imply that accounting data's association
with abnormal return varies as a function of the operative business cycle event. The evidence is not unambiguous however. The divergence of some of the results may be caused, in part, by wide differences in the operational definitions of "up" and "down" markets. Further, most previous studies have not used economically linked definitions of up and down markets, such as BVCP, thus weakening the ability to interpret findings. Finally, there have been relatively few studies in the area of business cycle effects. Much of the recent macroeconomic research, in keeping with the prevailing paradigm, does not view the classic business cycle as composed of discrete events. Relationships are thus assumed to be stationary across all levels of business activity. There is also recent, though limited, empirical evidence that suggests that any return variation related to business activity is primarily a product of systematic changes in the CAPM risk premium. Investors require this premium for holding the systematic risk associated with changes in business activity. If the risk premium is what changes across business cycle events, then return differences that relate to business activity would not be firm-specific. Therefore, associations of firm-specific factors with abnormal returns would not be expected to vary across business cycle events.

Another issue addressed is the fundamental question of whether accounting based data have been shown to have
predictive information content. Accounting-based data do appear to have some predictive information content. The extent of this predictive content, its robustness cross-sectionally and across time, and the degree and methods for which it can be applied in future investment decision contexts are questions that have been explored by only a few recent studies (Notably Ou and Penman, 1989a).
CHAPTER 3
THEORETICAL DEVELOPMENT

This chapter develops a theoretical model to posit that security risk, and therefore the PDU of accounting data, is affected by BVCP type. The return generation process, for any given security, is hypothesized to be intertemporally dependent on business cycle events. These events are viewed as discrete states (BVCPs) that are exogenous relative to firms and investors. The model also formalizes the notion of PDU.

3.1 The Return Model

Rosenburg and Guy (1976) theorize that economic events drive the covariance of security returns (beta), which, according to capital markets theory, is the primary determinant of return. Following Rosenburg and Guy, it is proposed that return generation is a function of macroeconomic events occurring in time. These macroeconomic events affect return by altering the expected individual cash flows of firms. Price is defined as the expected value of future cash
flows, discounted by some required rate of return (which reflects risk). Formally,

$$E[P_t] = E[\frac{CF_t}{(1+r)^t}],$$  \hspace{1cm} (3.1)

where $CF_t$ is cash flow in period $t$, $r$ is some required rate of return (assumed constant across time) and $E$ is the expectation operator. Now, return is

$$E[R_t] = E[\frac{P_{t+1} - P_t + D_t}{P_t}],$$  \hspace{1cm} (3.2)

where $P$ is as previously defined and $D_t$ is the dividend received in period $t$. If we assume, for the moment, that the Capital Asset Pricing Model (CAPM) holds, then non-diversifiable risk is the only risk for which investors expect to be compensated. All other risk can be diversified away. The CAPM then defines security return as

$$E[R_t] = E[R_f + \beta(R_{mt} - R_f) + \epsilon_t],$$  \hspace{1cm} (3.3)

where $R_f$ is the risk free rate, $R_{mt}$ is the return on a market portfolio of securities at time $t$, $\beta$ is the familiar beta

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coefficient and $\epsilon_t$ is a disturbance term at time $t$ that is an iid random variable $\approx N(0, \sigma^2)$. The variable in equation (3.3) that defines security risk and return is $\beta$. In accordance with Sharpe's model, beta is:

$$\beta = \frac{\text{Cov}(R, R_m)}{\sigma_m^2}, \quad (3.4)$$

where $\sigma_m^2$ is the variance of the market portfolio and all other terms are as previously defined. Because beta ($\beta$) is a function of the covariance between $R$ and $R_m$, it has been described as an estimator of "market sensitivity" of an asset.

3.2 The Interaction Theory

Now examine the question of the interaction of business cycle events with the process that generates individual firms' cash flows. The following is a simple example to demonstrate the theoretical support for this phenomenon. We begin by assuming cash flows are continuous. This is innocuous to the logic of CAPM. It may even be more theoretically correct, as large, well capitalized, and often internationally based firms have essentially continuous cash flows. That accounting reports produce data in discrete units is a measurement limitation, not a theoretical one. Imagine a single product
firm with fully divisible output. The firm is also a price taker. Assume a state of the world where, for the foreseeable future, there is no growth and no contraction of business activity. Assume all firms are identical in all respects. The firm's cash flow, required rate of return $r$, and distribution of all random variables are exactly like the market portfolio of firms. Finally, for simplification, the risk-free rate is fixed across time. Now the price of the security at time 0, which is just (1) stated in continuous terms, is

$$P_0 = \int_0^t E[CF_t(\Omega)] e^{-rt} dt,$$  \hspace{1cm} (3.5)

where $r$ is the discount rate of return, $CF$ is cash flow at time $t$, based on the information set $\Omega$. In this case, because of the assumption of a constant state of nature, $\Omega$ consists of

$$\frac{dCF_t}{dt} = 0.$$  \hspace{1cm} (3.6)

At time 1 the new price $P_1$ will therefore be equal to $P_0$, as before.
\[ P_1 = \int_0^\infty E[CF_t(\Omega)] e^{-\tau(t)} dt, \] (3.7)

In this contrived world, note that market return, \( R_m \), is exactly the same as \( R_t \). We may eliminate scale differences by assuming that \( P_0 \) in the respective denominators of security and market return is the same. If cash flow is identical, expected return must be also. For (3.3) to hold, beta(\( \beta \)) must equal 1. This is evident because the covariance term in equation (3.4) reduces to the variance of the market under these conditions.

If beta is a measure of sensitivity of the firm's cash flow to systematic events, then when business cycle-related conditions change, does beta change also? Let us return to equations (3.5) and (3.7), the prices of the firm's security at times 0 and 1 respectively. Suppose that the firm is like all firms, as before. The only exception is that there is some intrinsic characteristic of the firm that limits its capacity to utilize growth opportunities, should they exist. No other firm in the market is so hindered. During time 1 a systematic expansion develops in the sense that growth opportunities now exist in the marketplace, which the market portfolio of firms now aggressively capitalizes upon. This action produces an
accelerating income stream. The market portfolio's price at
time 1, conditioned on expansionary economic conditions, is

\[ (P_1 | x) = \int_0^T E[CF_t(\Phi)] e^{-tr(t)} dt, \quad (3.8) \]

where \( x \) represents the expansionary economic state and the
information set \( \Phi \) is such that

\[ \frac{dCF}{dt} = nb_t^{(n-1)}. \quad (3.9) \]

Here, \( nb_t \) represents some additional amount of income
obtained in period \( t \) by market firms as a result of their
capacity to capitalize on growth. The first derivative of cash
flow is now positive because it is accelerating through the
economic expansion. Equation (3.9) is also stated generally
such that cash flow acceleration \( (dCF/dt) \) may be increasing in
time, as a function of the constant \( n \). On the other hand, if
\( n \) equals one, then the cash flow change in time is constant
and equal to \( b \). Equation (3.3) then requires that beta be
less than one. To determine \( R_m \), we substitute into equation
(3.2) for the market portfolio. But \((P_1 | x)\) is greater than
\( P_1 \). Then \( R_m \) is greater than \( R_i \), because in the integral of

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equation (3.8) the market portfolio’s expected cash flows, based on the new information set $\Phi$, are greater for all $t$ than the former expectation based on information set $\Omega$. Yet the $i$th firm is constrained and cannot respond to growth, as other market firms can. So the former information set $\Omega$ still holds in determining $R_i$. $R_m$ is then greater than $R_i$ and beta must be less than one.

To see this graphically, consider Figure 1. Panel 1a graphs expected return onto growth opportunity during business-cycle associated market valuation changes (BVCPs). During expansions, as expected growth opportunities increase, so also does expected return increase. The slope is positive. As growth opportunities increase, return sensitivity increases for firms that are not constrained and have growth capacity. So market return grows while the constrained firm’s return does not. The area between the two returns is the difference, which beta maps across. In Panel 1b, return sensitivity (beta) is plotted against growth opportunities. As growth opportunities expand, the market portfolio earns greater return, while the constrained firm is unaffected. Beta must be less than one with the function negatively sloped. During periods when non-expansion, or recession, are being
discounted, growth capacity has no effect, because there are no growth opportunities.\textsuperscript{28}

Note that two conditions were required to create the sensitivity shift. First, the growth opportunity had to be present. Second, firms had to possess an intrinsic capability to take advantage of growth.

\textsuperscript{28}This of course assumes the phenomenon of systematic growth opportunity is unique to economic expansion.
Return

R_s = Market Portfolio's return
R_i = Return for firm i

GrowthCapacity

FIGURE 1
PANEL 1A
RETURN AND GROWTH OPPORTUNITY
DURING BUSINESS-CYCLE ASSOCIATED VALUATION CHANGES
\[ B_i = \text{Beta for Firm } i \]

**FIGURE 1**
**PANEL 1B**
BETA AND GROWTH OPPORTUNITIES DURING BUSINESS-CYCLE ASSOCIATED VALUATION CHANGES
3.3 The Interaction Theory and Accounting data

Return is thus a function of the interaction between firm specific factors and business cycle events, such as recession and expansion. Beta, because it is affected by this interaction, becomes functionally dependent on both. If return is a function of different macroeconomic events (in this case, economic expansion), and beta is a function of firm-specific factors, the return generating function can be modeled as follows:

\[ R_t = \alpha_0 + \delta_r f(\alpha_r, \beta_r(c_r)) + \delta_e f(\alpha_e, \beta_e(c_e)) + \epsilon \]  

(3.10)

where \( \alpha \) is the risk free rate, and \( \delta \) is a discrete coefficient that assumes a value of one when a particular business cycle event is occurring and 0 when it is not. The \( r \) and \( e \) subscripts refer to recession and expansion respectively. Beta is a function of \( c \), which represents firm-specific factors that drive the interactive association with macroeconomic events. If accounting data proxies for these firm-specific factors, then the association of accounting data and security return will also be a function of the operative BVCP type.
3.4 The Modeling of Recession and Expansion as Discrete States of Nature

Note that the coefficients in equation (3.10) are modeled as discrete variables, in keeping with the notion that recession and expansion can be viewed as discrete events. The reason for this can be seen in the previous example. If a systematic growth environment develops due to expansionary conditions, firms will activate endogenous processes associated with development and growth in order to exploit the new profit opportunities. From each firm's perspective, the degree of growth opportunity is irrelevant, so long as it far exceeds any one firm's capacity to supply. Therefore, the coefficients act like dummy variables and are "on" or "off". Which functions are "on" depends on which macroeconomic event is occurring. In the case of this study, either recession or expansion will be "on". Different expected returns will occur in each case.
CHAPTER 4

LITERATURE REVIEW

PART II

This chapter examines previous research concerning certain methodological issues that pertain to this study. These issues include: Choice of the appropriate statistical model when prediction is the objective and accounting data are used as independent variables; Variable selection for the accounting data sets that will be used in the multivariate analysis; and variable selection for the non-accounting data set. A separate review section follows for each of these three methodological concerns.

4.1 PROBABLISTIC DESIGNS USED IN PREDICTIVE ACCOUNTING RESEARCH MODELS

As stated, this research examined the multivariate questions of whether models based on accounting data vary in predictive accuracy across BVCP type. To test this, accounting-based models are constructed that proxy for the predictive decision usefulness of accounting data. The
question thus arises; what statistical model design is best suited to this purpose? Further, what probabilistic and sampling assumptions are reasonable in the context of the accounting-based prediction task?

This section addresses these questions by examining alternative statistical techniques that have been used for prediction in an accounting-based context. As part of this approach, for reasons explained next, the corporate failure research is reviewed extensively. Research that examines accounting variable associations to returns, market inefficiency and systematic risk sensitivity prediction is also incorporated into this review.

4.1.1 The Corporate Failure Prediction Research

The area of corporate failure research is rich in the application of predictive accounting-based models. This area thus provides an opportunity to examine previous applications of statistical models in accounting-based prediction problems, together with problems and limitations that were encountered. The limited theoretical support for variable selection in this area is also similar to return prediction research. There has been very limited theory in both of these areas to support the inclusion of specific accounting ratios into a given prediction model. As a result, much of the corporate failure prediction research utilizes variables that provide
empirically robust predictive usefulness as opposed to any other theory-based criteria.

The basic task of the corporate failure research is to predict the occurrence of the future event of corporate failure. As such, the dependent variable was typically nominal with only two mutually exclusive classes; Failed and non-failed. The following sections include an examination of several statistical models and methods that were used for failure prediction.

4.1.2 Univariate Methodologies

The seminal study in corporate failure was Beaver (1968). The study was univariate by design although numerous accounting variables were independently examined. Beaver first examined the means of accounting ratios for failed and non-failed firms. He employed "profile analysis" in the form of time series plots (one for each ratio) of the mean ratio values of each group. These plots revealed a marked deterioration of mean ratios in the failed group suggesting that accounting ratio data might have predictive power. Profile analysis was also very useful in depicting the average speed and timing of ratio deterioration. A great deal of

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29There were numerous difficulties in defining the operational meaning of "failure". The issue is not visited here because it does not directly concern the general prediction task.
general information was obtained from these plots, when surveyed over a range of ratios, because a pattern emerged as to when certain ratio groups (which purported to proxy for similar underlying constructs) became sensitive to impending financial failure. For example, net income to total assets, working capital to total assets and cash flow to total debt all react as early as four years before the event and have similar deterioration patterns (curvature and degree of slope) of sensitivity. On the other hand, the current ratio, thought to measure liquidity and protection from default, did not deteriorate until the year preceding failure. Profile analysis, while informative, particularly in the early stage of analysis, had limitations. For example, it did not take into account the dispersion of the variables being analyzed. Thus, inferential conclusions were not possible using only profile analysis.

Beaver also developed a "dichotomous classification test" by stratifying the full sample, and a sub-sample of the original failed and non-failed firms by values of the accounting ratio. The resulting arrays were analyzed, using arbitrary "visual inspection", for appropriate cutoff points that minimize misclassification. These cutoff points were used in classification rules (or on the rest of the original sample that had not been used to develop the cutoff rules). The classification rules predicted the group a firm belonged to:
failed or Non-failed. Comparisons were made between predicted group status and actual group status. The percentage error of misclassification became a measure of the overlap of failed and non-failed ratio distributions, as well as a measure of the predictive usefulness of the variable under study. An extension of this analysis utilized contingency tables that broke down the overall classification accuracy and inaccuracy into the four possible categories so that probabilities of misclassifying failed and non-failed firms could be assessed separately. In corporate failure, the costs of these two mistakes differ greatly. Further, the original sample had a much higher proportionate population of failed firms than did the true population. As a result, knowing individual errors was an important advancement in understanding the predictive usefulness of dichotomous classification. This technique was useful in quantifying prediction accuracy. It was also quite intuitive. The primary weaknesses of the approach included the inherent inability to use all available data in a multivariate environment and the ad-hoc "trial and error" nature of the constructed rules.

Beaver also prepared histograms of the ratios for each year previous to bankruptcy to test the assumptions of population distributional stability and type. In all instances, the ratios reflected a sharp skew to the right, while the distributions dropped off abruptly on the left.
Populations seemed to have very stable distributions across years. Beaver concluded that the ratio data were probably not normally distributed. He tested this conclusion with graphs of the cumulative density functions (CDF) of the ratios for failed and non-failed groups. The graphs depart sharply from linearity, confirming non-normality. Further, when the variables were transformed with square roots and logs, the underlying distributional skewness did not resolve. Beaver concluded that multivariate analysis, requiring normality assumptions, was probably inappropriate.

To summarize the univariate approach used by Beaver, the dependent variable, corporate failure, was dichotomized and this greatly simplified further analysis. Beaver utilized numerous data plots to determine distributional and mean behavior of the accounting ratios. He also employed tests of prediction accuracy that involved contingency tables, holdout samples and other validation techniques. Finally he examined accounting ratio distributions and found them non-normal and highly skewed to the right. Simple transformations did not correct this. Note that ratio analysis was originally developed (primarily in the twentieth century) for simple intra-firm comparisons. As statistical modeling and testing developed, the distributional non-normality of accounting ratios, which Beaver noted, have severely weakened their cross-sectional predictive statistical usage in a century when
gaussian techniques and assumptions have dominated empirical testing.

In addition to corporate failure prediction, univariate analysis has been used selectively to directly examine the association of stock returns to particular accounting ratios. This approach has the advantage of not imposing linear assumptions on the return association. For example, O'Connor (1973) took a sample of firm returns, divided into quartiles, and examined mean values for ten financial ratios to determine if they were statistically significant between groups. Similar grouping methods have been employed in many later studies, where various confounding affects, such as firm size, market risk, and P/E ratio, were first controlled for by using this grouping technique.\textsuperscript{30}

Another univariate approach that has been applied with accounting-based data involves the use of rank correlation statistics. As mentioned in earlier sections, Beaver, Kettler and Scholes (1970) used rank correlation coefficients to examine the relationship between beta estimates and various accounting-based variables.\textsuperscript{31} Firms were ranked into \( k \) portfolios based on a beta estimate. The rank procedure was

\textsuperscript{30}For example, see Basu (1983) and Fama and French (1991)

\textsuperscript{31}These include dividend payout, log of the five year change in book assets, book debt to book assets, the current ratio, the log of net book assets, the earnings "beta" and the standard deviation of earnings per share over nine years.

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repeated using the accounting variable to determine ranks. This was done for one period. Then rank correlations were computed for the period in which the ranks were determined and for a later hold-out period. Most of the variables showed little power in predicting betas, particularly for the hold-out sample. Three exceptions were book value of debt to book value of assets, the standard deviation of earnings over a nine year period and an accounting beta variable. This study is of interest because the design explicitly attempted to predict future betas and because the methodology involved rank statistics that may be less sensitive to non-gaussian distributional characteristics that most ratio data seem to have.

4.1.3 The Discriminant Analysis Research

The next applied technique that followed univariate analysis in corporate failure research was a seminal paper by Altman, that applied a multivariate statistical framework to the prediction of corporate failure. Altman employed discriminate analysis in an attempt to use more than one accounting ratio to predict those firms that failed and did not fail. Again, the dependent variable was dichotomous. While the multivariate aspect and the resultant use of a completely different statistical technique were innovative, the basic
prediction problem, design and sample limitations were the same as with Beaver (1968 and 1969). Further, the ratio skewness problem and lack of theory to support variable selection were virtually ignored by Altman.\footnote{Beaver did attempt to derive a cash "reservoir" theory to support selection of several of his variables. To date, this is one of the few efforts that have been made in the failure literature at a cohesive theory of failure.}

As to variable selection, Altman arbitrarily chose, as candidate variables for eventual inclusion in a working model, those that were basically popular and, in his judgement, "relevant" to the study. As for distributional assumptions, Altman employed a technique that assumes that the variables are multivariate normally distributed and that the variance-covariance matrix of all groups is the same. Neither of these assumptions were tested for validity. Accordingly, the severe distributional skewness and violation of normality that Beaver found was ignored and assumed away implicitly by arbitrarily employing multiple discriminant analysis. Altman's resulting discriminant function was able to accurately predict failure at rate greater than a naive model (predicting failure based only on overall population priors) for the first two years prior to the failure. Prediction in the third year and beyond was sharply lower. It is interesting to note that Altman's multivariate model, while far more complex and drawing on significantly greater information (potentially), predicted
failure only slightly better than Beaver's best univariate classification. The jump to a multivariate framework, while significant methodologically, did not improve predictive power substantively.

Numerous studies have since been performed using multivariate discriminant analysis (for example, see Wilcox, 1971; Blum, 1974; Deakin, 1972; Edminster, 1972; Sinkey, 1975; Altman, Haldeman and Narayanan, 1977; Kinney, 1973). This extensive research produced some improvement in the accuracy rate of predicting failure for at least the two years prior to failure (though this is difficult to fully assess because many studies did not test accuracy with holdout samples). Many studies attempted to improve on weaknesses in the early papers concerning failure definitions, failure proportions being different in the sample from real populations or to improve matching techniques and small sample problems with failed firms. Since these issues are not generalizable to this research, this study will not review these papers in detail. In a few papers, some efforts were made to deal with the distributional and stability problems of accounting ratios. These studies are now reviewed to examine these efforts.

Blum (1974) tested the accounting ratios he employed for evidence of multicollinearity. He found multicollinearity to be fairly low. He also examined a non-ratio model, using absolute accounting data (the data used was the same as for
the ratios). This method is of interest because the underlying accounting data may have different distributional characteristics that permit greater prediction power when used in gaussian-based statistical models. It turns out that the non-ratio model was not as accurate in the first year preceding failure, when compared to a similar ratio discriminant model. On the other hand, predictive accuracy was consistently more accurate in all later years. From Beaver (1968), discriminating ratio sets are different in the immediately preceding year, relative to other years. One possibility for Blum’s anomalous finding between absolute and ratio models is that the underlying variable set in earlier years, when used as absolute data, is more compatible with the discriminant model and is therefore more statistically appropriate.

Another study of interest was Edminster (1972). The initial variables considered were similar to the other failure studies, but multicollinearity was checked and variables were rejected when they were highly correlated with included variables (no multiple dependency tests were conducted). Edminster found a high rate of accuracy with his model in the year prior to failure.

A number of other design pitfalls in the use of discriminant analysis have limited the practical usefulness of this technique (Eisenbeis, 1977; and Zmijewski, 1984).
include the distributional problems discussed above, the finding that the variance-covariance matrix of failed and non-failed groups differs, incorrect variable specification, omitted variables in the design, lack of ability to determine a given variable's significance and appropriate sample selection. This last difficulty derives from the fact that failed and non-failed group samples are not randomly chosen and therefore do not represent an exogenous random sample. This can cause biases in parameter and probability estimations.

4.1.4 Multiple Regression with Least Squares estimation

A statistical model closely related to the discriminant model is the multiple linear regression model. This model was not generally applied in corporate failure research because the dependent variable is typically dichotomous. In other accounting-based prediction tasks, however, the method has had wide application. For example, Nerlove (1968) used various accounting variables as independent variables in multiple regressions designed to explain the variation in common stock returns. He reports $R^2$ ranging between .274 and .503 across

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33The dependent variable in gaussian linear regression is continuous. Linear models can be used with binary dependent variables, but the inherent nature of binary responses causes the distributional assumption of normality to be violated by design.
various subperiods between the years 1950-1964. Nerlove conducted no tests on distributional normality or homoscedasticity. He did conduct sub-period repetitions. Coefficient signs and magnitudes, as well as degrees of significance of variable coefficients, varied across different sub-sample periods. Predictive capacity of Nerlove's model is uncertain because no tests of predictive value were employed, such as error measurement of prediction with holdout samples, or jackknife tests of prediction accuracy.

A later study (O'Connor, 1973) examined the predictive usefulness of ratio data in predicting return ranks of equity securities. Stock returns were computed over one, two, and five year windows during the years 1950-1966 for 127 firms. Using correlation analysis, O'Connor reduced an original group of 33 variables to a set of ten variables that seemed to capture most of the "information available". These were then analyzed univariately and in multiple regression analysis. Three separate dependent variables were used in separate stepwise multiple regressions: An unadjusted after-tax rate of return; An industry adjusted rate of return; and a market-adjusted rate of return. R² for the various models ranged from

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34 In fact, one part of the study involved the inclusion of a numerous set of dummy variables for industry type. These variables far outweighed, in number, the accounting ratio data. Because of their dichotomous nature and mutual exclusiveness, these variables, by design, added collinearity into the model.
.07998 for the three year model to .32243 for the five year model when the dependent variable was the unadjusted after-tax rate of return. Similar results obtained for the models that used the other dependent variables. Firms were then ranked based on predicted return from the linear regression and rank correlations observed between predicted ranks and ranks from hold-out sub-samples.\(^{35}\) Results were compared to a simple "naive" model that ranked firms based on the previous period's result. O'Connor found that relationships did not appear stable across either time or cross-sectionally. Further, the ratio-based models were not able to predict return rankings, even when the dependent variable was adjusted for market and industry effects. O'Connor concluded that accounting ratios did not appear to be predictively useful, at least in predicting return ranks, when used in multiple linear regression models.

Rosenburg and McKibben (1973) also used gaussian multiple regression to examine the association between numerous independent variables, including eleven market-based measures and thirty-three total variables. Because the purpose of the study was to find explanatory real determinants of beta, no hold-out sample was used. Rosenburg and McKibben's findings are ambiguous concerning the role of individual variables

\(^{35}\)Hold-out samples were cross-sectional (within period) and time variant (across time periods).
because collinearity in the multivariate environment may have affected coefficient values (Myers, 1977). Rosenberg and McKibben do provide evidence which supports, to the extent it is interpretable, Beaver, Kettler and Scholes' finding that financial leverage and growth in sales and earnings may be important determinants of return generation (Beaver, Kettler and Scholes, 1970).

Gaussian linear multiple regression methodology has also been used to detect the association of specific accounting-based ratios with security and market returns, before and after controlling for market risk (for examples, see Rozeff, 1984; Fama and French, 1987; Bhandari, 1988). These studies were generally not developed specifically as prediction models. Instead they were primarily aimed at detecting market inefficiency or examining ways to supplement beta as a proxy for risk. Significant associations were found for variables such as book to market value, e/p ratios, dividend yield and debt/equity.

4.1.5 The Logistic Regression Research

The numerous theoretical and methodological inconsistencies associated with the application of discriminant analysis to an accounting-based dichotomous prediction task led corporate failure researchers to search for other statistical and probabilistic models whose implicit
assumptions could more easily fit the data. Because the prediction task involved a dichotomous dependent variable, conditional probabilistic models began to be employed, beginning in the mid to late 1970s. A representative paper that applied maximum likelihood estimation to bankruptcy prediction with a conditional probabilistic model known as LOGIT was Ohlson (1980). Ohlson chose LOGIT because it avoids many of the theoretical problems associated with discriminant analysis. In particular, LOGIT requires no distributional assumptions on any of the independent variables. Additionally, statistical significance of the various independent variables can be interpreted under certain conditions with tests that employ asymptotic theory. The outcome space could also be represented along a continuum of probabilities as opposed to a "Z" score that lacked direct probabilistic interpretation and was used primarily for simple classification into two nominal groups.\(^{36}\)

The logistic regression model is given by:

\[
P(x_i) = \frac{1}{1 + e^{-x'_i \beta}}
\]  

\(^{36}\)It is possible to produce probabilistic estimates with discriminant analysis, but the estimates have not proven as reliable as with probabilistic models (Martin, 1977).
where $B'_j$ is a $j \times 1$ vector of coefficient estimates, $X_{ij}$ is a $j \times 1$ vector of independent variable observations for the $i$th observation and $P(x_i)$ is the probability that the observation firm with the $x$ vector of observations will fail. As can be clearly seen, this model yields probabilistic estimates rather than absolute assignments into two previous population groups (though it can still be used for this, with appropriate cutoff rules). Lacking distributional requirements on the $j$ independent variables, and lacking assumptions of equal variance-covariance matrices from two populations that are assumed to be distinct, the model seems to fit the accounting based prediction task better than gaussian-based models (given the variable distributions' extreme right skewness property). This was particularly true for failure work, where low sample sizes of failed firms causes difficulties with population priors and overall small samples. The Logistic model also has several interesting prediction properties. First, $P(x)$ is increasing with $B'X$ and is therefore relatively easy to interpret. Also, $P(x)$ does not increase at a constant linear rate. Instead, the logistic cumulative density function is a sigmoid curve that asymptotically approaches zero and one. Collins and Green (1982) point out that this provides the model with a "threshold" quality in that at a certain value level, the independent variable vector causes the probability
to rapidly move close to one. Conversely, at high values, little further damage occurs, thus resolving the problems associated with ratio fractions "blowing up".

Surprisingly, when Ohlson used the LOGIT model, together with classification rules based on symmetrical .05 cutoffs, he found that the model was not able to substantively increase the overall classification accuracy relative to previous discriminant analysis studies. As noted earlier, the logistic framework is, on theoretical grounds, seemingly better suited to failure prediction than linear discriminant models, especially given the severe skewness of accounting ratio data. Ohlson therefore found the lack of substantive improvement in classification accuracy provided by LOGIT disappointing. He concluded that the prediction task may be robust across estimation procedures. Zavgren (1983) notes several potential problems in Ohlson's study, including ad hoc variable selection and multicollinearity among variables. Zavgren extended Ohlon's study by extending the variable set and using two different conditional probabilistic models (The original LOGIT and PROBIT as well). Zavgren chose variables that were based on previous factor analytic studies of ratio variability (Pinches, Mingo and Carothers, 1973; Pinches et al, 1975). By using variables derived from orthogonal factors, Zavgren attempted to control the multicollinearity issue. Zavgren found similar results to Ohlson for the first year prior to
bankruptcy and similar classification accuracy results to several discriminant studies for all earlier years. The results suggest that the LOGIT and PROBIT conditional probability models were not very useful in resolving the severe distributional problems associated with accounting ratio data.

Collins and Green (1982) and Hamer (1983) confirm the comparability of the LOGIT and the discriminant model. Hamer's study (1983) is particularly interesting because it controls somewhat for the many methodological differences inherent in the various bankruptcy studies, thus providing more confidence in her cross-study comparisons of accuracy rates. Hamer (1983) also compared quadratic discriminant models, which permit violation of the assumption of equal variance-covariance matrices among population groups. The results of this model were generally poorer than either LOGIT or the linear discriminant models. This would be expected since the quadratic model is known to be very sensitive to violations of normality.

While the studies above confirm comparability of estimation models, the unanswered questions remain. Why didn't LOGIT perform appreciably better, given the stronger adherence to assumptions? Or did the LOGIT model induce entirely new assumptions, such as the shape of the cumulative density
function itself, that were themselves arbitrary, at least in failure prediction, and thus unsupported by the data?

LOGIT has been used successfully in predicting future stock returns with accounting ratio data by other researchers in other areas of interest. For example, Ou and Penman (1989), in examining market inefficiency and the usefulness of fundamental analysis, used a LOGIT model in a two-pass regression design that supported firm selection into long and short investment portfolios. Positions were taken in these two portfolios so that wealth outlays and receipts offset, thereby creating a zero net investment trading strategy. Ou and Penman were able to generate substantive net returns over two year windows with this approach.

Of interest was the methodological innovation in firm selection for the trading strategy. Two regression stages were conducted. The first stage regressed a detrended dichotomous earnings variable onto various accounting ratios that were suggested by a "survey of financial accounting and financial analysis textbooks". Those that were most significant in this univariate pass were then carried forward into a multiple regression stage. The multiple regression stage incorporated 16-18 independent variables, of the original 68 variables, into another LOGIT model. The dependent variable was the same as the first univariate LOGIT regressions. Ou and Penman then used a stepwise procedure to select the "best" possible
prediction model for each of two separate subperiods. The probabilistic projections made by the LOGIT model were transformed by Ou and Penman into trading rules by using arbitrary cutoffs that assigned firms into long and short categories. Note that the primary purpose of this study was to support a zero net investment trading strategy. This trading strategy was designed to test market efficiency.³⁷

Because the objective was to test market efficiency, the LOGIT models used in this study were used to predict the direction of detrended earnings (as opposed to a direct prediction of stock returns). This dependent variable was expected to be less sensitive to changes in a firm's ex-ante discount rate of return, and more sensitive to changes in future cash flows. In addition, because the problem was now cast into a dichotomous framework, a conditional probabilistic model, such as LOGIT, which requires no distributional assumptions on the accounting-based ratio variables, could now be introduced.

As noted, the Ou and Penman research addressed the theoretical issue of market efficiency and did not focus

³⁷If the long and short portfolios were similar in risk characteristics, then return on the straddle (net zero investment) would be expected to be zero, ex-ante (otherwise, arbitrage opportunities, such as this strategy, would exist). If the market was inefficient, then an observed ex-post return over long windows would be evidence of this. Ou and Penman found abnormal returns over windows of two years and longer.
directly on decision usefulness in predicting future stock returns. The study is important however to the issue of statistical design needed for this research because, unlike the bankruptcy research mentioned earlier, the LOGIT model, as used here, appeared to discriminate well in ultimately predicting high and low return performers.

4.1.6 The Effect of Normality Violations on Failure Prediction Accuracy

As mentioned, conditional probability models were appealing in bankruptcy research because distributional assumptions are not required for the independent variables. Accounting-based ratios are known to be highly skewed and non-normal. In particular, observations regularly occur that are several standard deviations from the mean. Investigation of these data points has revealed that they do not appear to be artifacts of measurement error. This suggests that extreme ratio observations are not outliers. They may instead derive from non-normal probabilistic functions of the underlying ratio distributions (Deakin, 1976).

As mentioned earlier, despite the apparent non-normality of accounting data, models that do not require normality assumptions on the independent variables have not appeared to outperform gaussian-based models in predicting corporate failure. This surprising result has been explored by several
researchers. Richardson and Davidson (1984) found that "sick" firms exhibit a great deal of moment instability in several financial variables. In an earlier simulation study, Richardson and Davidson (1983) found that when skewness and kurtosis characteristics were added to normal simulated data populations (to an extent that modeled "real" data) there were significant changes in the accuracy of failure prediction. On the other hand, they appeared to be relatively minor in scope. They concluded that deviations from normality probably canceled out in a multivariate context, and/or were mitigated by the bounded nature of accounting ratios, following Lachenbruch et al (1973).

Chinganda and Subrahmaniam (1979), in a related study, found a direct association between the amount of population group overlap and the effects on classification accuracy of non-normal distributions. Hopwood, McKeown and Mutchler (1988) compared prediction accuracies of LOGIT, PROBIT and discriminant models before and after a transformation and outlier detection process developed by Frecka and Hopwood (1983) and Gasko and Green (1981). Essentially, ratio distributions were subjected to square root transformations, followed by a heuristic deletion of "outliers" until skewness was no longer significant. They found that prediction accuracy improved marginally with the use of these modified
distributions and concluded that all the statistical models were somewhat sensitive to violations of non-normality.

In conclusion, previous research is ambiguous as to the effect of non-normality on the predictive capacity of statistical models, at least in the failure prediction context. LOGIT and PROBIT conditional probability models, because they require no distributional assumptions on the independent variable set, have been utilized in a variety of accounting-based predictive applications. In general, they have not substantively improved classification results in corporate failure prediction. In other applied contexts, such as predicting future earnings, the conditional probability models have demonstrated somewhat stronger results, at least empirically. In addition to nominally classed, and typically binary, dependent variable requirements, the LOGIT models also impose theoretic assumptions of a specific functional shape. These assumptions often have no sound theoretical or intuitive basis for many ratios to which they are applied. This lack of theoretical grounding may partly explain the marginal performance of conditional probability models in accounting research to date.
4.2 THE ACCOUNTING-BASED DATA SET

This section of the literature review examines accounting-based data that have been found to be significantly associated with stock returns. The related issues of data reduction and ratio analysis are also considered. Extensive use of statistical models of accounting-based variables can put too much demand on a cross-sectional sample (Ou and Penman, 1989). Data reduction procedures are therefore examined to see how they have been utilized in accounting-based prediction tasks. Further, multi-collinearity can affect the predictive ability of a model when prediction is made outside of the space of the observed independent variable values (Myers, 1977).

Accounting based ratios have often been used in prediction tasks because accounting-based data usually exhibit cross-sectional size trends in their absolute values. Ratios, because they deflate accounting data with size proxies, have traditionally been used to control for firm size in across-firm comparisons.\(^{38}\) At issue is whether size should be controlled for, and if so, whether ratio construction is the most predictively effective means for accomplishing this.

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\(^{38}\)Another far more complex task of ratio analysis is to compare the relative value of an account per unit of some other account. For example, the current ratio compares the level of current assets per unit of current liabilities.
4.2.1 Accounting Based Data and Stock Returns

There is a notable lack of theoretical support for the inclusion of specific accounting-based data into models that predict stock returns. As a result, researchers are left with the difficult problem of defining a non-theory based selection rule. Typically, the choice is somewhat arbitrarily based on the popularity of variables, their intuitive reasonableness (from the point of view of the researcher) or precedent in previous research.\textsuperscript{39} Researchers typically use one of two basic selection approaches. In one approach, the selection problem is tackled with an exhaustive approach aimed at examining all plausible variable candidates (Nerlove, 1968; Ou and Penman, 1989). These studies are reviewed in section 4.2.2, which discusses data reduction procedures. In a second, more focused approach, a few individual variables have been extensively studied. These include the book value of a firm, the book to equity ratio, dividend yield, debt/equity ratio, earnings and the E/P ratio, higher moment variables and cash flow variables. The literature concerning these variables is now reviewed.

\textsuperscript{39}For example, Altman (1968) uses these criteria, as does Beaver, Kettler and Scholes (1970).
4.2.1.1 Book Value and Book to Equity

Rationale behind the use of book values and book to equity ratios typically relates to theories of market inefficiency. Book values are based on historical cost-based numbers, typically with little or no recognition of intangibles, while market values represent current valuations of all firm assets. The relative levels of book and market equity may therefore represent pricing inefficiencies, either due to "overvalued" market values (Rosenburg, Reid and Lanstein, 1985) or "undervaluation" due to functional fixation on book value (Harris and Ohlson, 1990). Harris and Ohlson (1990), for example, suggest that the market incorrectly "fixated" on book values in pricing oil and gas properties, thus creating arbitrage profit opportunities that can be exploited by simple trading rules. They found that abnormal returns can be earned from these rules. Another theoretical approach uses book value to represent the "stock of net resources" (Easton and Harris, 1990). Following Ohlson (1989), Easton and Harris (1990) test the theory that security valuation is a function of weightings on earnings and book value where the weights sum to one. Their empirical results support this theory.

Stattman (1980) and Rosenberg, Reid and Lanstein (1985) found that returns on stocks are associated with the ratio of
book value to common equity. Fama and French (1991) found that firm size and book value to market equity explain most of the cross-sectional variation in stock returns associated with beta, size, leverage, book to market equity and earnings/price ratios.

4.2.1.2 Dividend Yield

Dividend yield, defined as the dividend per share payout divided by price, has been advanced as a significant predictor of stock returns. One theory used to explain this relationship is that dividend yields are proxy measures for the risk premium in equity securities (Rozeff, 1984). Another hypothesis is that "stock prices are low relative to dividends when discount rates and expected returns are high and vice versa, so that dividends/price varies with expected returns (Fama and French, 1988). There is substantive evidence that stock returns vary with dividend yield (Campbell and Shiller, 1987; Rozeff, 1984; Ou and Penman, 1989). This variable also appears to be particularly important when the return measurement window is long (Fama and French, 1988).

4.2.1.3 Debt/Equity Ratio

A number of theories have associated the weaknesses in the association of beta with stock returns to a measurement error problem. Financial ratios have been hypothesized to be
better proxies for equity risk than a direct measure of beta. One ratio that easily relates to the measurement of this risk is the debt/equity ratio. Beaver, Kettler and Scholes (1970) do determine that leverage and beta estimates are significantly associated. Bhandari (1988) finds that common stock returns are associated to the debt/equity ratio, even after controlling for beta and firm size.

4.2.1.4 Earnings and E/P ratio

A extensive body of research has found that earnings and stock returns are positively associated (e.g. Ball and Brown, 1968; Easton, Harris and Ohlson, 1989; Beaver, 1970). Stock reaction around earnings announcement dates has been the focus of a large body of empirical research employing the event methodology. Market efficiency research has found delayed price reaction to earnings announcements (Hand, 1990; Bernard and Thomas, 1989 & 1990). In addition to earnings, earnings variability has also been found to be positively associated with stock prices (Beaver, Kettler and Scholes, 1970). Finally, Basu (1983) found that earnings/price ratios explained variation in stock returns, over and above that accounted for by size and beta.

In general the size effect and e/p association with security returns has been found to be highly correlated. A number of researchers, in addition to Basu (1983), have tested
these two variables jointly and have attempted to disentangle the two effects (Reingenam, 1981; Cook and Rozeff, 1984; Banz and Green, 1986). Jaffe, Keim and Westerfield (1990), using a longer period sample, seemingly unrelated regression techniques, and variables that discriminated for January and non-January periods, found that the size and price effects mostly occurred during January whereas the e/p effect occurred throughout the year. Fama and French (1991) confirm that earnings/price is associated with security return variation.

Ball (1978) argues that earnings/price may be a proxy for other unknown factors in security returns. Campbell and Shiller (1988) found that a long moving average of real returns is a powerful predictor of returns, particularly when return is measured over several years.

4.2.1.5 Higher Moment Variables

No extensive work on variance based independent variables has been done. The earliest work was Blum (1974) who looked at the standard deviations of certain ratios such as net income and net quick assets/inventory. Dambolena and Khoury (1980) used a more extensive set of variance-based independent variables, in addition to mean-based variables. They were able to significantly improve classification accuracy with the addition of the new variables. Hamer (1983) compared Blum's (1974) model, which included ratio variability variables and
found no consistent significant difference in the model over other prediction models. In summary, ratio variability may contribute to the prediction task, though the issue is not clear. Further, there is no assurance that the failure results are generalizable to other prediction tasks.

4.2.1.6 Cash Flow Variables

A few studies have looked at accrual versus cash flow variables to determine which set is most appropriate to the failure prediction task. Casey and Bartczak (1985) found no evidence that cash flow ratios are better suited to prediction than accrual based ratios. On the other hand, predictive value of the cash flow variables were comparable, suggesting that they represent a viable alternative to accrual based ratios.

4.2.2 Data Reduction

Accounting information sets, as represented by a firm's annual financial statements, have extensive data items. Traditionally, since the development of ratio analysis by Dupont in the 1920s, accounting data have been employed in the form of financial ratios that relate one account balance to another. These ratios were designed to measure various underlying firm characteristics such as liquidity,
performance, and profitability, for within firm and industry comparative analysis. Because of the extensive nature of accounting information data sets and the redundancy of many financial ratios in capturing underlying firm characteristics, data reduction techniques are typically employed by researchers to limit the number of variables entering statistical models. In particular models, such as LOGIT, that offer the opportunity to assess the significance of individual variables, may be greatly improved when multicollinearity is reduced or eliminated. This can also improve performance in the prediction task (Myers, 1990).

Data reduction in corporate failure took three approaches. The first was more or less ad hoc and involved a cursory survey of which ratios were most popular or "seemed" most relevant to the researcher. Most early failure studies took this approach (For example, Beaver, 1968; Altman, 1968; Deakin, 1972; Edminster, 1972; Blum, 1974; Ohlson, 1980). The second approach was more theoretical and involved some theory as to which variables should be selected for study. Very few studies used this approach. Two exceptions are Beaver’s seminal study that used a reservoir theory (Beaver, 1966) and Wilcox’s Gambler’s ruin model (Wilcox; 1971, 1976).

Finally, a third approach utilized previous studies of the common covariance structure of accounting information systems. An example is Zavgren (1983) who chose her variables
by using previous research of the covariance patterns detected by Pinches, Mingo and Caruthers (1973) and Pinches et al (1975). Pinches, Mingo and Caruthers (1973) utilized a factor analytic methodology to detect common underlying factors among ratio data sets. They used log transformations on all ratios and oblique rotation, which results in factors that are not necessarily orthogonal. Oblique rotation can be more useful in identifying theoretical constructs because factors are not constrained to be orthogonal, which is probably more realistic. On the other hand, oblique methods of rotation are used less frequently and are subject to some controversy concerning interpretation (Hair, 1987). Pinches, Mingo and Caruthers found seven factors, which they defined as (1) return on investment, (2) capital intensiveness, (3) inventory intensiveness, (4) financial leverage, (5) receivables intensiveness, (6) short term liquidity, and (7) cash position. Pinches et al (1975) found that the factors identified in the earlier study were robust across time. Richardson and Davidson (1984) confirm this result, at least for "well" firms, noting that ratios tended to load on the same factors (using orthogonal rotation) for this group.

Data reduction has been applied in other accounting research areas. As mentioned earlier, the Ou and Penman (1989a) study used a data reduction procedure. This was used first on the full data set to select accounting-based ratios...
for inclusion into a subsequent multivariate LOGIT model. Ou and Penman began with 68 accounting ratios. In the first pass univariate LOGIT regression, they identified highly significant accounting ratios that could predict the direction of detrended future earnings. Those that were most significant in this univariate pass were then carried forward into a multiple regression stage. Of the 16-18 independent variables carried forward, Ou and Penman found only 6 variables that were sufficiently robust to be included in each of two subperiod regressions. These were as follows: (1) the change in inventory/total assets; (2) change in dividends per share; (3) change in capital exp/total assets, one year lag; (4) return on total assets; (5) operating income/total assets; (6) and repayment of long term debt as a percentage of total long term debt. The data reduction techniques used by Ou and Penman permitted the reduction of an original expansive data system to a small robust set of predictive accounting-based independent variables. Ou and Penman found that large accounting-based ratio sets placed too much demand on data pooled cross-sectionally and in time. Many ratios, such as the quick and current ratios, were also closely related and would have exhibited high multicollinearity, thus weakening prediction power outside the range of the observed X variable matrix.
A couple of weaknesses in the Ou and Penman (1989a) data reduction methodology deserve mention here. First, the univariate first pass design greatly limited the number of considered models in the multiple regression. Relatedly, some of the variables, while not as significant (or even insignificant) in the univariate context, may have been found to contribute significantly in the multivariate regression. This, for example, occurred in Altman's seminal bankruptcy prediction model (Altman, 1968). Several of the variables Altman finally included were not the most significant, when tested independently. Another problem is the use of stepwise regression to choose the final model. Stepwise is a heuristic procedure that iteratively alters a model's variable composition and tests for the added significance of new variables and variables previously included. This technique, while sometimes necessary in large data sets, does not consider a large number of possible model candidates with different variable composition. Better techniques, such as all possible regression, with summary statistical criteria such as an adjusted $R^2$, analogous to Cp, and Press were not utilized by Ou and Penman.\textsuperscript{40} Ou and Penman (1989b) repeat their reduction technique and LOGISTIC modeling in a follow-up study.

designed to determine the incremental information content of accounting numbers over price changes and the price to earnings ratio. The "Pr" probabilistic measure, produced by the prediction model, after data reduction, is shown to have incremental information content.

Ou (1990) uses the same data reduction techniques as in Ou and Penman (1989a) to develop an LOGIT earnings prediction model. The model is then used to predict the direction of future detrended earnings, assess prediction accuracy, and establish that non-earnings accounting data have incremental PDU over current earnings changes in predicting future earnings changes. The data reduction techniques she employs reduce an initial set of 61 ratio predictors to just 8 variables by again using univariate LOGISTIC significance levels as a screening criteria. The technique serves to reduce data demands and permit more simplistic model contraction from a large set of candidate variables.

4.2.3 Ratio Analysis

Financial ratios have long been used by researchers to predict stock returns and associated systematic risk (Nerlove, 1968; Beaver, Kettler and Scholes, 1970; O'Connor, 1973; Ou and Penman, 1989). One of the major reasons for the use of financial ratios, in lieu of absolute financial data, is to
control for the cross-sectional systematic effects of size. Lev and Sunder (1979), however, show that ratios will control for size only under very "restrictive" conditions. One of these restrictive conditions is that the numerator variable must be strictly proportional to the size proxy. This is because ratios do not allow for a fixed constant. As a result the intercept of the linear relation is forced through zero. 41 There can also be no measurement error because a stochastic noise term is not defined in the assumtional model form of a financial ratio. Note also that in the presence of homoscedastic error, large firm measurement errors will be small relative to small firms. This measurement bias weakens cross-sectional ratio comparability. Further, if the ratio is affected by other variables' values, then this may bias the ratio because the other variables may also be affected by size and these associations are not being controlled for. A final restrictive limitation of the use of financial ratios to control for size is that they implicitly assume a linear relation between the variable and firm size. If this assumption does not hold, the financial ratio will not serve as an adequate size deflator.

41Consider the value x/y = B, where x is a variable of interest, y is the size proxy and B is some constant. The relation can be re-written x = By. Note that this relation contains no intercept or noise term.
Lev and Sunder (1979) also raise the question of what size proxy to use. If the proxy is also affected by the phenomenon being studied, then its use as a control deflator becomes far more difficult. Further, the size proxy should be chosen based on theoretical and statistical criteria and properties. There may also be substantial measurement error considerations in the choice of a particular size proxy. Yet these issues are rarely discussed in accounting research. The choice of an appropriate financial ratio seems to be primarily driven by custom and tradition.

Lev and Sunder (1979) also discuss the problem of correlation between ratios. Correlation between two variables, x and y, is not generally equal to the correlation between \( \frac{x}{z} \) and \( \frac{y}{z} \) where z is some size deflator. Therefore it is possible to identify correlations that do not exist in the original variables. Lev and Sunder identify this problem as "model misspecification" as opposed to "spurious correlations". The argument reduces to the fact that financial ratios are very different variables from the composite raw variables from which they are constructed.

Financial ratios have interpretive problems when negative numbers enter the numerator or denominator because these sign changes can reverse the interpretation of magnitude.

Financial ratios are also used to control for industry specific factors and to determine relative account amounts.
(for example, current assets per dollar of current liabilities). In the case of industry control the choice of an industry standard, from which to compare, depends to a great extent on the cross-sectional distributional properties of ratios. Unfortunately, little is known about these properties beyond the fact that most financial ratios have non-normal cross-sectional distributions (Deakin, 1976).

A last comment concerns the absolute values of ratios in cross-sectional comparisons. Financial ratios were developed extensively by the Dupont Company in the 1920s for use in intra-firm diagnoses of productivity and efficiency. Ratios are known to be informative primarily at the within-firm and within-industry level. The actual values of ratios have no theoretical comparative meaning outside of their relative values within firm and within industry. Therefore, there is no benchmark value for most ratios, from which to compare. As a result, financial statement analysis textbooks almost always discuss ratios in comparative terms (A value relative to last year's value or to a similar firm's value). The actual values of financial ratios, particularly in cross-sectional studies, are therefore not interpretable outside of the comparison context.
CHAPTER 5
DESIGN AND METHODOLOGY

5.1 INTRODUCTION

This chapter presents the design, hypotheses, expected results, data description and test procedures for the empirical portion of this study. Accounting and stock return data for the period from 1969 to 1983 are examined for evidence to support or reject implications that derive from the interaction theory presented in chapter 3. The chapter begins with a formalized definition of the return interval labeled "Business-cycle related Valuation Change Periods (BVCPS). The dependent variable used in the empirical study is next described. Hypotheses that derive from the interaction theory of chapter 3 are then set forth in section 5.4. A description of the data set and screening procedures follow in section 5.5. Section 5.6 briefly describes the general research approach. Finally, in sections 5.7 and 5.8, the univariate and multivariate research design, models and testing procedures are presented. Results of the univariate and multivariate procedures follow in chapter 6.
5.2 DEFINING MAJOR RECESSION AND EXPANSION MARKET-RELATED EVENTS

A formal definition of recession and expansion, and the periods during which these systematic events are discounted into security prices, is required to empirically test for evidence of the interaction theory described in chapter 3. As discussed in section 2.2 of the literature review, past research has produced conflicting results concerning the effects of market direction on systematic risk and security return associations. As noted in section 2.2, a possible cause of these conflicting results is that definitions of bull and bear markets (or equivalently, up and down markets) have generally not linked market direction and underlying real macroeconomic events. This study seeks to utilize an economically linked definition of market direction that permits time-varying associations and incorporates real underlying macroeconomic phenomenon into its construction.

For this project we consider only major business recessions and expansions. Three major recessionary periods are studied. These are the recessions of 1969-1970, 1974-1975 and 1981-1982. Similarly, three expansionary periods are studied. These are the periods of 1971-1973, 1976-1980 and 1982-1987. These events, and the dates of their occurrence, were identified by using the National Bureau of Economic Design and Methodology 104
Research's (NBER) determination of recession and expansion events.\textsuperscript{42}

5.2.1 Defining Business cycle related Valuation Change Periods (BCVPs)

As mentioned in the literature review, several previous studies have used the NBER designations of recession and expansion to define up and down markets. This definition has several advantages, including linkage to a real macroeconomic event and exogenous determination by a recognized authority on business cycles. It does suffer, however, from an implicit assumption that investors price the expected effects of a business cycle event during the event. Observations of stock market behavior around business cycle peaks and troughs indicate that investors’ expectations change some months prior to the actual occurrence of the recession or expansion (Piccini, 1980). Recessions and expansions are thus typically preceded by discounting periods labeled herein as Business-

\textsuperscript{42}One exception concerns the NBER determination that two recessions had occurred during the periods from January, 1980, to July, 1980, and July, 1981, to November, 1982. The first period was of very limited duration and intensity in comparison to other periods. It also fell within close proximity to the severe recessionary period of 1981-1982. For these reasons, the event days during this period were grouped together with the latter recessionary period. These together were defined as the third major recession-associated BVCP.
cycle related Valuation Change Periods (BVCPs). As noted in Chapter 1, BVCPs are periods of major systematic price revaluations that result from new information about unfolding business cycle events. Accordingly, the BVCP is expected to occur immediately preceding or coincident with the triggering business-cycle event. As such, the BVCP conceptually represents a definition of bull and bear markets that is economically linked to a triggering business cycle event.

BVCPs are similar if the same type of triggering event is associated with each BVCP. For example, if two BVCPs each precede or are coincident with a macroeconomic recession, then the BVCPs are similar because the triggering events in both cases are the same type. Conversely, if the triggering events are different, so that one BVCP is recession-associated and the other is expansion-associated, then the BVCPs are dissimilar.

Figure 2 contains a graph of the Standard and Poor's eight-quarter normalized moving average return of 500 composite stocks (S&P500) overlaid for the years 1967-1987 with the real Gross National Product statistics, as described above, for the same period. Note that most market movements lead or are coincident with major GNP changes. These changes occur most often as trends; The trend intervals are fairly long, perhaps as news of a particular event is fully received, assessed, and discounted by all investors.
FIGURE 2
REAL GNP AND S&P500 STOCK INDEX
(8-QTR STANDARDIZED MOVING AVERAGES)
5.2.2 Identifying BCVPs

To identify a BVCP period, the high and low points of S&P 500 stock index trends that were coincident with or immediately preceded the NBER determinations were graphically detected. These were used as event boundaries for the BVCP. BVCPs are therefore only identified when the following conditions occur: A major recession or expansion event, as defined by NBER, occurs; and a major price revaluation occurs at approximately the same time as the underlying macroeconomic event. BVCPs are also free of the unrealistic assumption that investors discount recession and expansion events as they happen.

Trading intervals also do not overlap. Figure 3 lists the various identified BVCP intervals, notation for each, and boundary dates.

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43 The S&P500 stock index was chosen because it is diversified, widely followed, and publicly available in many media sources. Another candidate, the Dow Jones Industrial average, is not as diversified. It is also specific only to industrial stocks. The CRSP equally weighted market index might be a possibility, but it is probably not widely used outside the academic community. In any case, all of these indices varied only by a few days as to boundary dates. The long event windows preclude the possibility that index choice could make a substantive difference in the SAR metric.
<table>
<thead>
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<th>Beginning date</th>
<th>Ending date</th>
<th>Event Type</th>
</tr>
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<tr>
<td></td>
<td>Nov 27, 1980</td>
<td>Aug 9, 1982</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mar 28, 1980</td>
<td>Nov 26, 1980</td>
<td></td>
</tr>
</tbody>
</table>

**FIGURE 3**

**NOTATION AND BOUNDARY DESCRIPTIONS**

**BUSINESS-CYCLE ASSOCIATED VALUATION CHANGE PERIODS (BVCPs)**

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5.3 THE DEPENDENT VARIABLE: STANDARDIZED ABNORMAL RETURN (SAR)

This study sought to determine if firm-specific factors, as proxied by accounting data, interact with BVCP type to affect stock returns. The focus has therefore been on association shifts that occur across BVCP type. The definitional cyclicality of recession and expansion events implies that expected returns estimated from data in the previous BVCP period would not reflect the current BVCP return function in equation (3.10).

Shifts in association across BVCP type are therefore detectable in cumulative abnormal return for the event period, just as with any event study. The study is constrained to be cross-sectional in nature however, because the long event windows BVCPs invoke reduce the number of possible time-series observations to only six (averaging more than 1.5 years in length) per firm and these vary in length. BVCPs also vary in severity and direction of slope. In addition, the BVCP events occur at the same time for all firms. These BVCP-related peculiarities cause several econometric concerns, including the following: (1) biases in parameter estimation; (2) the potential occurrence of confounding events because of event clustering; (3) history

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44The NBER defines these events by identifying peaks and troughs of business activity.

45Assuming expected returns are based on previous BVCP data only.

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and maturation effects associated with return intervals of different length; (4) possible problems of error dependency across long return intervals; and (5) scale differences in the cumulative abnormal returns of BVCPs. The operational definitions of the abnormal return metric is presented next. The definition is constructed to address some of these econometric concerns.

5.3.1 Definition of Standardized Abnormal Return (SAR)

5.3.1.1 Capturing the Association Shift

Recall that equation (3.10) was:

\[ R_t = \alpha_0 + \delta_r(\alpha, \beta_r(c_t)) + \delta_e(\alpha, \beta_e(c_t)) + \epsilon, \]  

(5.1)

where \( \alpha \) is the risk free rate, and \( \delta \) is a discrete coefficient that assumes a value of one when a particular business cycle event is occurring and 0 when it is not. The \( r \) and \( e \) subscripts refer to recession and expansion, respectively. Beta is a function of \( c \), which represents firm-specific factors that drive the interactive association with macroeconomic events. If accounting data proxy for these firm-specific factors, then the association of accounting data and

\[ \text{DESIGN AND METHODOLOGY} \]  
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security return will also be a function of the operative BVCP type.

Assume, for example, the equation (5.1) can be perfectly measured ex-post. This takes all "noise" and stochastic properties out of the model. Then from equation (5.1) one of the return processes we might measure using previous dissimilar BVCP data is:

\[ R_t = a_0 + \delta_t f(\alpha_t, \beta_t(c)), \]  

(5.2)

where all terms are as previously described. Assume that the true return process is:

\[ R_t = a_0 + \delta_t f(\alpha_t, \beta_t(c)), \]  

(5.3)

where all terms are as previously defined. Equation (1) will be estimated as:

\[ R_t = a_0 + \delta_t f(\alpha_t, \beta_t(c)) + \epsilon, \]  

(5.4)

where \(a\) and \(b\) are estimators for \(\alpha\) and \(\beta\), \(\epsilon\) is defined as the abnormal return generated by the shift in functions that occurred within equation (3.10), and all other terms are as
previously defined. The abnormal return is the difference between the "true" model, equation (5.3), and the estimated model, equation (5.2). Canceling terms, and assuming perfect estimation, we have:

\[ e = f(\alpha, \beta_1(c)) - f(\alpha, \beta_2(c)), \]  

(5.5)

where all terms are as previously defined. This would be detected in the abnormal error term of equation (5.4).

5.3.1.2 Abnormal Return and Interval Length

One approach to measuring the shifts detected by abnormal return in equation (5.5) is to measure cumulative abnormal return for the entire BVCP. There are several arguments in favor of this approach. First, accounting ratio data across the entire time period of this study is available only annually. Further, the dynamics of recession and expansion news events are not well understood. The daily BVCP discount rate may therefore vary across BVCPs. To capture the effect of BVCP type and fully control for variations in the discounting rate across BVCP events, a holistic view of the recession associated and expansion-associated BVCPs is necessary.
Further, investors are assumed to buy and hold securities throughout the BVCP. For these reasons cumulative abnormal return over the BVCP seems reasonable as an appropriate dependent measure.

A number of statistical issues constrain this ideal choice, however. First, the return intervals of BVCPs vary in length. The intervals also vary systematically in length across BVCP type. The expansion-associated BVCPs are always longer than recession-associated BVCPs, and average 1152 trading days as compared to 421 days during recessions. To control for history and maturation effects associated with interval length differences, the BVCP intervals should be of the same length.

Given that all BVCPs should be truncated to an equal interval length, how long should the window be? Long windows are more likely to be contaminated by exogenous events. There is also a greater possibility with extremely long windows (in the case of expansion-associated BVCPs, these may exceed 4 years) that cross-sectional dependencies will affect the validity of inferential tests (Bernard, 1989). Therefore, a relatively short window is statistically preferred and improves the interpretation of results. On the other hand, differences in discounting rates and information arrival and processing across BVCP type may bias a very short window towards differences in association. Short windows may not
capture an event-related association shift. Finally, investors are assumed to use buy and hold strategies, and this implies reasonably long return intervals.

As noted, this study seeks to determine if firm-specific factors, as proxied by accounting data, interact with BVCP type to affect stock returns. The focus is therefore on detecting any association shifts that occur across BVCP type. If these shifts partly occur as a function of information arrival differences, this may also affect the PDU of accounting data. The interval lengths are therefore set to an arbitrary length of one year. This interval length is long enough to support the notion of a buy and hold trading strategy. Further, it is a reasonable length of time in which to expect that investors have detected the occurrence of a recession or expansion. On the other hand, each window is of equal length, thus controlling for length-related non-stationarities, and is not so long as to provoke major statistical concerns.

Should the windows be measured beginning at the onset of the BVCP or at some other point during or near the end of a BVCP? The most likely period during which a parameter shift would occur is in the change from one BVCP type to another. Therefore, this study measured the one year interval beginning at the beginning boundary of the BVCP as defined earlier.

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5.3.1.3 Problems With the Market Model Definition of Abnormal Return

As seen in the previous sub-section, abnormal returns derived from a market model definition of expected return should capture the association shift. The use of an expected estimate of return based on the market model would prove problematic in this kind of study. First, deriving unbiased estimates of the alpha and beta parameters in equation (5.2) would require an estimation period outside the scope of the long event windows being observed. This would create additional data demands. Second, to capture the BVCP type shift, estimation periods would have to exclude other similar BVCP intervals. Estimates of beta, as discussed earlier, are known to be degenerate across time. In order to exclude similar BVCPs, estimation intervals would vary across BVCPs in terms of proximity to the event window, adding noise to cumulative abnormal return measurements. Return interval length is also longer in expansion-associated BVCPs than recession-associated BVCPs. Therefore, beta estimation may bias results across BVCP type.

Finally, estimates of beta have been shown to have little or no association to average returns after controlling for the Banz-Reinganum size effect (Fama and French, 1992). The empirical usefulness of an estimate of beta has also been
challenged on theoretical grounds by Roll (1977 and 1980). Therefore, estimates of beta may not adequately describe the expected returns specified in equation (5.1). If accounting data capture some portion of the systematic risk (beta) parameter of equation (5.2) that the estimate of beta in equation (5.4) misses, then cumulative abnormal return associations would vary across BVCP type even if there were no interaction with the BVCP event itself. For example, in this case, risky stocks would show higher abnormal returns in expansion-associated BVCPs and lower cumulative abnormal returns in recession-associated BVCPs, ceritus peribus. The accounting ratio proxy would therefore show significant associations to cumulative abnormal return, but the direction of any association would reverse in a symmetrical fashion across BVCP type.

5.3.1.4 The Size-Adjusted Abnormal Return Metric

Another definition of abnormal return that has been used by previous researchers is size-adjusted return (Bernard and Thomas, 1989 and 1990). The metric is:

\[ AR_s = R_s - R_p, \]  

(5.6)
where $R^*_t$ is the equal-weighted mean return for day $t$ on the NYSE/AMEX firm size decile of which firm $i$ is a member at the beginning of the Calendar year. All other terms are as previously defined. Firm size is measured by the market value of common equity.

This measure has a number of statistical advantages. In particular, the portfolio formation periods that determine the size adjustment will be in close or equal proximity to the BVCPs being examined, irrespective of BVCP type. Another important advantage of size-adjusted abnormal returns is that they may more fully control for stationary systematic risk than estimates of beta. As mentioned earlier, Fama and French find that firm size seems to capture the explanatory power of beta estimators (Fama and French, 1992). On the other hand, a disadvantage of the size-adjusted abnormal return measure is that the "size effect" has been established empirically but not theoretically. The reasons for "the size effect" are thus not well understood. Size-adjusted abnormal returns may be insensitive to association shifts as described by equation (5.5) if they also control for part or all of the interactive effect that is being examined. On the other hand, most of the accounting ratios used in this study are adjusted for size and may already be desensitized to any interactive effect resulting from size differences.
5.3.1.4 Standardization of Cumulative Abnormal Returns

For the reasons discussed in the previous section, size-adjusted abnormal returns are used in this study. The abnormal returns are cumulative from the beginning of a BVCP through day 250. Abnormal return for each BVCP is therefore:

\[ CAR_i = \sum_{t=1}^{250} AR_{i,t}, \quad (5.7) \]

where all terms are as previously defined, \( CAR_i \) is the cumulative abnormal return for firm \( i \), \( t=1 \) is the first day of the BVCP and 250 is the total return interval length of the BVCP event window.

If all BVCPs were of the same magnitude, this metric would be sufficient. BVCPs vary in magnitude and severity, however. Since this study focuses on firm-specific factors as opposed to BVCP differences, the variable defined in equation (5.7) must be standardized to remove magnitude differences across BVCPs and restate abnormal return in relative terms. The estimate of the dependent variable— the size-adjusted, standardized abnormal return, hereafter referred to as SAR— is therefore:
\[ SAR_i = \frac{\text{CAR}_i - \frac{1}{N} \sum_{j=1}^{N} \text{CAR}_j}{\sigma_{\text{CAR}}} \]  

where \( \sigma_{\text{CAR}} \) is the standard deviation of the CARs for a given BVCP, \( N \) is the number of cross sectional firms in the sample and all other terms are as previously defined.

5.3.1.6 SAR Summary

In summary, the size-adjusted standardized cumulative abnormal return is used in this study as the dependent variable. The length of each BVCP event window is fixed at 250 trading days to control for interval length differences across BVCPs and permit clearer interpretation of results. Size-adjusted abnormal return is becoming a widely used measure in event studies. It may control for stationary systematic risk sensitivity as well as some cross-sectional dependencies. The variable is standardized to remove BVCP-specific differences in magnitude.

5.4 STATEMENT OF HYPOTHESES

5.4.1 The Statistical Model

Various statistical models were reviewed in Section 4.1. Section 4.1.4 contains a review of multiple linear regression applications that have been applied to the return prediction
problem. The dependent variable in this research is continuous and is approximately normally distributed. Further, the "threshold function" imposed by some models, such as the logistic, is arbitrary and unsupported by theory. Conditional probability models, such as Logistic, have not achieved appreciably better results in most accounting applications. This study therefore uses the standard multiple linear regression model with least squares estimation.

5.4.2 The Effect of BVCP type

The interactive theory proposed in chapter 3 posits that security risk, and accounting variables associated with this risk, are affected by recession-associated and expansion-associated BVCPs.

If these shifts occur, as reflected in equation (5.5) of the previous section, associations of accounting variables with abnormal returns should vary across BVCP type. On the other hand, if we assume that accounting data associations with subsequent BVCP SARS are not affected by BVCP type, the size-adjusted abnormal return's association with accounting data should not vary across BVCP type. The following null hypothesis states this implication:

H1) The association of accounting-based variables and SARS will not vary across recession-associated and expansion-associated BVCP types.
5.4.3 The Non-Stationarity of Predictive Accuracy in an Accounting-based Information System

If associations of accounting data with subsequent BVCP SARs vary univariately across BVCP type, then it follows that a multivariate accounting-based model's prediction accuracy may vary across BVCP type. From this inference the following hypotheses are set forth:

H2a) A "best" prediction model that is estimated with a set of accounting ratios as independent variables and recession-associated BVCP SARs will not predict future recession-associated BVCP SARs significantly better than expansion-associated BVCP SARs.

H2b) A "best" prediction model that is estimated using a set of accounting ratios as independent variables and expansion-associated BVCP SARs will not predict future expansion-associated BVCP SARs significantly better than recession-associated BVCP SARs.

The "best" accounting ratio-based model refers to a model selected using the STEPWISE sequential selection procedure. Only accounting ratios found to be consistently associated with SARs of a given BVCP type enter the models at this stage of testing. This limits the testing of many possible models and weakens somewhat the generalization of results. On the other hand, data reduction is crucial at the multivariate

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level because too many variables place excessive demand on the data in this kind of cross-sectional study (involving 18 years of needed data).

5.4.4 The ACCOUNTING-BASED Information set

The accounting-based information set tested must be bounded because inclusion of all possible accounting information, across all possible time, places too much demand on the data. Section 4.2 of the literature review contains a description of accounting ratio data that have been found by previous research to be significantly associated to stock returns in cross-sectional studies. Further, Ou and Penman (1989) show an abnormal return using a zero-net investment strategy based on the initial input of 68 accounting ratio variables.

This study bounds the accounting information set to the 68 accounting variables used by Ou and Penman, together with 14 other variables suggested by previous research and reviewed in section 4.2. These variables are listed in Table 1. The accounting-based ratio variables are computed from financial statement data available in the annual report immediately preceding each recession or expansion-associated BVCP. As described in detail later in Chapter 5, these variables are examined first in simple linear regression for significant associations to returns in the immediately subsequent and "one
similar period ahead" BVCP. Variables are also examined for robustness of association across similar type BVCPs. Variable transformations are also examined, including higher order terms, standardized values, rank values, logs and square roots. Accounting ratio variables are then selected for inclusion into multiple regression model tests using the results of these simple regression procedures.
### Table 1

**The Accounting Information Set**

1. Current ratio  
2. Change in #1  
3. Quick ratio  
4. Change in #3  
5. Days sales in accounts receivable  
6. Change in #5  
7. Inventory Turnover  
8. Change in #7  
9. Inventory to total assets  
10. Change in #9  
11. Change in inventory  
12. Change in sales  
13. Change in depreciation  
14. Change in dividends per share  
15. depreciation/plant assets  
16. Change in #15  
17. Return on operating equity  
18. Change in #17  
19. Change in capital expenditures/total assets  
20. #19, 1 yr lag  
21. Debt to equity ratio  
22. Change in #21  
23. Long term debt to equity  
24. Change in #23  
25. Equity to fixed assets  
26. Change in #25  
27. Times interest earned  
28. Change in #27  
29. Sales to total assets  
30. Change in #29  
31. Return on total assets  
32. Return on closing equity  
33. Gross margin ratio  
34. Change in #33  
35. Operating profit to sales  
36. Change in #35  
37. Pretax income to sales  
38. Change in #37  
39. Net profit margin  
40. Change in #39  
41. Sales to total cash
<table>
<thead>
<tr>
<th>No.</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>42.</td>
<td>Sales to accounts receivable</td>
</tr>
<tr>
<td>43.</td>
<td>Sales to inventory</td>
</tr>
<tr>
<td>44.</td>
<td>Change in #43</td>
</tr>
<tr>
<td>45.</td>
<td>Sales to working capital</td>
</tr>
<tr>
<td>46.</td>
<td>Change in #45</td>
</tr>
<tr>
<td>47.</td>
<td>Sales to fixed assets</td>
</tr>
<tr>
<td>48.</td>
<td>Change in production</td>
</tr>
<tr>
<td>49.</td>
<td>Change in research and development expense</td>
</tr>
<tr>
<td>50.</td>
<td>Change in R&amp;D to sales</td>
</tr>
<tr>
<td>51.</td>
<td>Change in advertising expense</td>
</tr>
<tr>
<td>52.</td>
<td>Change in advertising/sales</td>
</tr>
<tr>
<td>53.</td>
<td>Change in total assets</td>
</tr>
<tr>
<td>54.</td>
<td>Cash flow/total debt</td>
</tr>
<tr>
<td>55.</td>
<td>Working capital/total assets</td>
</tr>
<tr>
<td>56.</td>
<td>Change in #55</td>
</tr>
<tr>
<td>57.</td>
<td>Operating income/total assets</td>
</tr>
<tr>
<td>58.</td>
<td>Change in #57</td>
</tr>
<tr>
<td>59.</td>
<td>Change in total uses of funds</td>
</tr>
<tr>
<td>60.</td>
<td>Change in total sources of funds</td>
</tr>
<tr>
<td>61.</td>
<td>Repayment of long term debt as a percentage of total debt</td>
</tr>
<tr>
<td>62.</td>
<td>Issuance of long term debt as a percentage of total debt</td>
</tr>
<tr>
<td>63.</td>
<td>Purchase of treasury stock as a percentage of total stock</td>
</tr>
<tr>
<td>64.</td>
<td>Change in funds</td>
</tr>
<tr>
<td>65.</td>
<td>Change in long term debt</td>
</tr>
<tr>
<td>66.</td>
<td>Cash dividend as a percentage of cash flows</td>
</tr>
<tr>
<td>67.</td>
<td>Change in working capital</td>
</tr>
<tr>
<td>68.</td>
<td>Net income/cash flows</td>
</tr>
<tr>
<td>69.</td>
<td>Total assets to market equity</td>
</tr>
<tr>
<td>70.</td>
<td>Change in #69</td>
</tr>
<tr>
<td>71.</td>
<td>Total assets to book value</td>
</tr>
<tr>
<td>72.</td>
<td>Change in #71</td>
</tr>
<tr>
<td>73.</td>
<td>Book value to market equity</td>
</tr>
<tr>
<td>74.</td>
<td>Change in #73</td>
</tr>
<tr>
<td>75.</td>
<td>earnings/price ratio</td>
</tr>
<tr>
<td>76.</td>
<td>Change in #75</td>
</tr>
<tr>
<td>77.</td>
<td>Retained earnings/total assets</td>
</tr>
<tr>
<td>78.</td>
<td>Change in #77</td>
</tr>
<tr>
<td>79.</td>
<td>Dividends/total assets</td>
</tr>
<tr>
<td>80.</td>
<td>Change in #79</td>
</tr>
<tr>
<td>81.</td>
<td>Cash/total assets</td>
</tr>
<tr>
<td>82.</td>
<td>Change in #81</td>
</tr>
</tbody>
</table>
5.5 THE DATA SET AND SCREENING PROCEDURES

5.5.1 Data Collection and screening

The source of the return data used in this study was the CRSP daily return database for NYSE and AMEX firms. In the initial collection step, daily returns were summed for all individual NYSE/AMEX stocks for which complete return data on a given BVCP were available. The data were screened for numerical codings indicating insignificant values, missing values, etc, as well as other data imperfections. SARs were then computed for each remaining security using the formulas in section 5.3.

5.5.2 Data Sources and Screening

The source of the accounting ratio data were the COMPUSTAT annual, primary and tertiary file tapes. This database includes selected data obtained from the annual financial statements of public corporations. The accounting data required to compile and compute the 82 accounting based financial ratios (listed in Table 1) were collected and screened for missing observations, numerical codings such as those described above for CRSP, and zero values where these values would be used in denominators of the ratios to be
computed. The accounting data were obtained from the nearest annual report (based on its date) available prior to the onset of the subsequent BVCP. This procedure does not correct for "look ahead" bias that has affected some other event studies. On the other hand, there is some variation and uncertainty about the information release dates of the accounting data that are used. Any adjustment would be arbitrary and presumptive of when the information was released to the market. Any look-ahead bias adjustment may have, therefore, downward-biased the results towards an insignificant finding, thus weakening the power of any tests. Figure 4 presents the measurement intervals for the accounting ratio data, together with the SAR event interval.
\[ \begin{array}{cccccccc}
& t_5 & t_4 & t_3 & t_2 & t_1 & t_0 & t_1 & t_2 & t_3 & t_4 \\
\end{array} \]

xxxxxx  = SAR event interval

......  = Accounting ratio measurement intervals

*****  = Accounting change ratio intervals

FIGURE 4
VARIABLE MEASUREMENT INTERVALS
5.5.3 Ratio Computation and File Procedures

Accounting ratios were then computed. The variables that measured accounting ratio percentage changes used absolute values in the denominators to control for the partial derivative sign reversal that would occur otherwise.

Following the accounting ratio computation procedures, the two data sets, accounting ratios and SARs for the various BVCPs, were merged and screened for missing BVCP SARs. Only accounting ratio observations that had subsequent BVCP SARs were retained for further analysis.

The data were analyzed for each separate BVCP as well as pooled across similar BVCPs. When data were pooled, each firm could conceivably have two observations per BVCP type.

The data were not adjusted for survivorship bias by inclusion of delisted firms. The study was centered towards the prediction of SARs in future BVCPs. Accordingly the prediction task centers on surviving firms. Further, to control comparability of tests across models, the data requirements in the multivariate analysis include complete data availability for all of the BVCPs under study. This necessarily precludes non-surviving firms. While the lack of adjustment for survivorship bias permits the development of a model tailored to this kind of longevity study, it also limits...
the generalizability of the results and thus represents a limitation in this research.

5.6 GENERAL RESEARCH DESIGN

The empirical portion of this study proceeded in two stages. The first stage consisted of the simple regression analysis and included univariate tests of hypothesis (1). The methodology of this stage is discussed in section 5.7. The second stage was the multiple regression analysis. The purpose of this stage was to test hypothesis (1) in a multiple regression context and to test hypotheses (2a) and (2b). The methodology of the multiple regression stage is presented in section 5.8.

The first stage, the simple regression analysis, was conducted with two objectives in mind. The first objective was to univariately test hypothesis (1) of section 3.2, following the general approach of Beaver (1966). The second objective was an exploratory effort to determine which accounting ratio variables to include in the second stage of the study (the multiple regression analysis), following the procedure used in Ou and Penman (1989).
5.7 THE SIMPLE REGRESSION ANALYSIS

The simple regression procedures were conducted as follows. First, the subsequent size-adjusted BVCP SAR metric was regressed onto each accounting ratio. Tests were made to detect the significance, strength, direction and robustness of any associations. Following this, tests were made of associations of transformed accounting ratio data with subsequent BVCP SARs. Transformations examined included square roots, logs, ranks, higher order terms, and standardized ratios. Finally, the results of these procedures were analyzed and compared to determine which variables should enter the multiple regression analysis. The following sub-sections detail these simple regression procedures and tests.

5.7.1 Simple Regressions Using Pooled Data

After the data were collected and screened, as described in the previous sub-section, BVCP SARs, pooled by BVCP type, were univariately regressed onto each of the 82 accounting ratio variables in separate univariate regressions. To test hypothesis (1), the coefficients for each of these regressions
were separately tested for significance. The recession-associated and expansion-associated results were then compared and contrasted. Criteria for these comparisons included sign, magnitude, and significance of the coefficient and adjusted $r^2$ of the model. In each regression and test, all observations for which that particular accounting ratio and the associated SARs were available were included. Each variable was therefore tested independently of all other accounting ratio data.

5.7.2 Simple regressions: Using Unpooled Data

Following these pooled regressions, accounting ratios that were found to be significant were again regressed with BVCP SARs. This time however, the data were not pooled. Thus, for each BVCP type, two sub-period associations were available, excluding the holdout samples. The purpose of

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*Hypothesis (1a) can be viewed as 82 separate hypotheses: One for each of the 82 accounting variables under study. Because each is in effect a separate test, no experiment-wise error control procedures were introduced. Note that approximately 2 of the 164 tests would be expected to be significant on the basis of chance (at the .01 level of significance). SARs are only approximately normal. Returns have been shown to derive from stable pareto distributions (thus having fat tails relative to the normal). As a result, t-test results must be interpreted with caution.*

*The holdout samples were excluded in the original tests of hypothesis (1a) and (1b) because the results of these procedures also served as criteria for variable inclusion in multivariate models. One purpose of these models was to predict SARs in the holdout BVCPs.*

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these second-pass regressions was to further test hypothesis (1) and to determine accounting ratio candidates for inclusion in the multiple regression analysis.

5.7.3 Validity of Test procedures

The tests on the coefficients from the univariate regressions employed standard t-tests of coefficients. In order for these inferential tests to be interpreted literally, abnormal return data would have to be cross-sectionally independent. As mentioned earlier, King (1966) and Cohen and Pogue (1968) documented evidence that cross-sectional return-based data may be cross-sectionally dependent due to model misspecifications relating to industry effects. Bernard confirms the existence of these cross-sectional dependencies and shows that cross-sectional studies with long windows may be particularly susceptible (Bernard, 1987). Bernard demonstrates that the standard errors used in inferential tests may be biased downward by several factors, particularly with large sample sizes. In addition, studies with large samples are found to be more exposed when cross-sectional data dependencies exist.

On the other hand, the standard errors used in the denominators of the univariate t-tests may also be overstated because of model misspecification. In general, abnormal return variation that could be explained with other accounting ratios
tends to increase the residual error, thus making any t-tests that employ this standard error highly conservative.\textsuperscript{48} The two effects may offset to some extent. In any event, the univariate tests consist of the entire population of NYSE/AMEX firms, less any that did not include data over 80\% of a given BVCP interval and any that did not contain COMPUSTAT data for a given BVCP interval.\textsuperscript{49} The univariate stage is also designed to be primarily exploratory in nature. As a result, the tests should be viewed simply as descriptive of this sub-population. They are primarily presented as a basis for comparison and should not be interpreted literally.

### 5.7.4 Data Availability Across All BVCPs

In the case of certain variables, the data were not available for the entire time period of the BVCPs under study. This was typically due to differences in accounting reporting standards across the full time period of the study. For

\textsuperscript{48}Coefficient values can also be biased. As a result, the univariate procedures primarily represent a data-reduction screen for subsequent multivariate study. This approach has been used by other researchers, including Ou and Penman (1989). Direct univariate interpretation is primarily comparative.

\textsuperscript{49}The 80\% cutoff is quite arbitrary. The purpose of the cutoff was to assure that sample observations were exposed to most of the BVCP event. The cutoff also assured that samples would not materially differ across samples in percentage length of exposure to BVCPs. While slightly increasing survivorship bias, this procedure mitigates bias resulting from systematic differences in BVCP exposure.
example, variables related to the Statement of Cash Flows, or its predecessor, the Statement of Changes in Financial Position, typically have no data for the first two BVCPs under study because the statement was not a required financial report at that time. Further, some variables are not available during the first BVCPs because the COMPSTAT database did not contain them. An example is advertising expense. This variable is included only in the univariate analysis to more fully test hypothesis (1).

5.7.5 Regression Model: Pooled and UnPooled

The regression model was:

\[ SAR_{it} = \beta_0 + \beta_1 AR_{it} + \epsilon_{it}, \quad (5.9) \]

where \( SAR_{it} \) is the SAR for the ith firm. The \( x \) and \( t \) subscripts, describe the BVCP, where \( x \) is the BVCP type and \( t \) is the period within each type. The \( x \) subscript always refers to either "recession-associated" or "expansion associated". \( AR_{it} \) is the related accounting ratio variable computed from the most recent financial statement data available previous to the onset of the BVCP.
5.7.6 The Regression Error Term and Reasonableness of Assumptions of Normality and iid.

The $\epsilon$ is a random error term assumed to be independently and identically distributed normal with mean of 0 and variance $\sigma^2$. Because the research design is non-experimental, this assumption is an approximation that may not strictly hold. The sample is not randomly chosen. Further, as mentioned earlier, there is evidence from previous research of cross sectional dependencies in return data (King, 1966; Cohen and Pogue, 1968; Bernard, 1987). There is also no theory to support an assumption that the errors are identically distributed cross-sectionally. Lastly, the assumption of distributional normality is at best only approximate and other distributions for return data have been theorized to exist (Mendelbrot, 1963; and Fama, 1965).

5.7.7 Controls Provided By the Unpooled Test Procedures

The unpooled tests are included in the design to permit further testing of hypotheses (1), as stated earlier. Further tests are needed because the pooled results may be biased by confounding event clustering and therefore be sample-specific. Within each pooled BVCP type, there are only two event observations and they occurred concurrently across all firms. There is thus a possibility of confounding event clustering.
The unpoole d tests provide an opportunity to obtain further evidence by checking for consistency of associations during different similar BVCPs. Return intervals of BVCPs are spaced out over eighteen years from 1969-1987. Economic conditions were highly variable over this time. For example, high rates of inflation were experienced during a few of these years while relatively low rates occurred during others. The unpoole d tests, because they examine BVCP associations separated by intervals of several years, provide partial evidence for or against confounding event clustering.

5.7.8 The Transformation Procedures

As discussed earlier, accounting ratio data are generally not normally distributed. In particular, ratio values are constrained to non-negative values and often "blow up" when denominator values approach zero. As a result, ratio associations are often highly skewed to the right and cutoff on the left. Yet extreme values of accounting ratios may not infer equally extreme changes in SARs. Therefore, accounting ratio associations with subsequent SARs may not be linear. Models that can account for these non-linearities in association may be more accurate in the prediction task. For example, the natural peculiarities of ratio data may explain why Ou and Penman (1989) were able to develop successful
trading rules based on accounting data associations to detrended earnings as applied in a logistic model.\textsuperscript{50}

The remarks above suggest that use of accounting ratios in linear regressions may require transformation of the raw variables to more fully capture the PDU of accounting data. Accordingly, a number of ratio transformations were attempted within the context of the linear regression models that were employed. The ratio transformations that were tested included logs, square roots, squared and cubed terms. The log and square root transformations were tested because these have often been employed in previous studies that used accounting ratio data. The higher order terms were tested to examine the possibility of non-linear associations that can be modeled in linear regressions.

5.7.8.1 Transformations To Extract Relative Information Contained in Accounting Ratios

No theory currently exists that can fix constant market-wide ratio values as benchmarks for comparative cross-sectional tests. Perhaps as a result, most accounting ratios have instead found traditional use in comparative procedures such as horizontal analysis. In this manner, accounting data

\textsuperscript{50}In the logistic curve, ratio values primarily affect probabilities within a certain narrow range, thereby causing a kind of "threshold" effect. See section 4.1.5 of the literature review.
are used to compare a firm's performance to its past performance or to that of its competitors. As such, the absolute value of the accounting ratio is not meaningful, per se. Rather, it is the relative value of the ratio compared to previous values, other accounts, or current industry and cross-sectional norms that provide meaning.

Further, the Euclidean distances between observed ratio values may not be meaningful. The lack of theory for an "ideal" cross-sectional value, combined with the "blow-up" phenomenon of ratio data, may make such distances meaningless. Yet without transformation to remove these effects in linear regressions, the distances may obscure meaningful information contained in a firm's relative cross-sectional rank. Ratios may thus require rank transformation in order to be useful. This may explain the popular use in academic research of portfolio approaches whereby firms are ranked into an arbitrary number of portfolios based on ratio values. To explore these possibilities for ratio use, standardized values and rank transformations were also examined. Standardized values of accounting ratios were examined to control for possible location shifts in ratio values across BVCPs, as well as changes in dispersion. Standardization is a comparative

\footnote{Earnings to price ratios are an example. See Basu (1983).}
procedure because it provides relative scaling for independent
variables within each BVCP.

Similarly, ranks also provide relative values by mapping
absolute values onto a uniform scale that ignores distance
between values. The rank transformations proceeded as follows.
The values of each accounting ratio were ranked by size from
lowest to highest within each BVCP (unpooled by type). Then
the rank number was assigned as the value for that ratio. This
procedure, while removing scaling differences and controlling
for the "blow-up" phenomenon, causes a technical violation
because a continuous variable is now mapped to a discrete
rank. Technically, then, dummy variables would be needed for
each rank. On the other hand, the rank set includes more than
one thousand rank values in most cases and is therefore
assumed to be continuous for simplification purposes.

5.8 THE MULTIPLE REGRESSION METHODOLOGY

Following the simple regression procedures, multiple
regression analysis was conducted. Only those variables that
met the simple regression criteria were further analyzed in a
multiple regression context. These criteria included: data
availability across all BVCPs; significant association to
subsequent BVCP SCARS in the pooled tests; and significant
associations to subsequent BVCP SCARS in all similar BVCPs in
the unpooled tests.
The variables that passed these screens were then subjected to a series of procedures designed to test hypotheses (1), (2a) and (2b). These procedures are described in the following sections.

5.8.1 Multiple Regression Confirmation Of The Simple Regression Findings

The simple regression findings are useful only when accounting ratios are used individually. In an environment of market efficiency, it is plausible to assume that investors would take advantage of accounting ratio data contemporaneously in a multiple variable context. Further, the simple regression results may be driven by model misspecification to the extent that single regressor models are underfit and variables are correlated with any omitted variables (Myers, 1990). To address these issues, hypothesis (1) was also tested in a multiple regression context. The accounting ratios that met the screens mentioned above were used as independent variables in multiple regression models. As with the simple regression analysis, subsequent BVCP SAR was the dependent variable. Similarly, regressions were first conducted using data pooled by BVCP type. Then the regressions were repeated using unpooled data to provide evidence that confounding events were not driving the results.
The analysis proceeded as follows. The two sets of accounting ratios suggested by the univariate findings (listed in Table 9, panels A and B) were analyzed separately as possible candidates for inclusion in a "best" regression model, using recession-associated pooled BVCP data for the variables in Table 9, panel A, and expansion-associated pooled BVCP data for the variables in Table 9, panel B. Variables were selected for inclusion in a "best" regression model using the STEPWISE sequential selection procedure. The two sets each produced one "best" model using this procedure.

A multiple regression was then estimated on the two "best" models for each BVCP type, using pooled BVCP data not reserved for use as a holdout sample. Two regressions were conducted for each of the two "best" models: One regression used recession-associated pooled BVCP data to estimate coefficient values; the other regression used expansion-associated pooled BVCP data. Coefficient values and signs were then tested for confirmation of the univariate findings with respect to hypothesis (1).

\textsuperscript{52}The STEPWISE sequential selection procedure is a heuristic entry and deletion process involving partial F-tests. Although it does not consider all possible models, it is a useful and widely applied technique, particularly when large variable sets prohibit the application of all-possible regression techniques. A criterion F value is selected for entry and deletion. For this study the entry and deletion F critical values were those for the F distribution with appropriate degrees of freedom and significance at the .15 level.
Tests were also conducted to determine the existence and extent of any multicollinearity. These tests are outlined in detail in section 5.8.1.1. The presence of severe multicollinearity can cause instability in the values and signs of individual regressor coefficients, thereby weakening the reliability of individual variable tests of hypothesis (1) in a multivariate context. Using the findings of these tests, variables were deleted from the model where necessary to improve collinearity diagnostics and interpretability of individual coefficient signs and magnitude. The coefficient values of the remaining variables were then re-tested, if necessary, for confirmation of the univariate results.

A number of other econometric issues may plausibly have accounted for any results found. First, accounting ratio distributions may contain significant numbers of outliers, as discussed in Chapter 4. It is possible that outlier observations in the data set account for most of the significant associations that were found. The ratio association shift across BVCP type may therefore not be robust cross-sectionally. To test for this, outliers were defined and deleted in a procedure described in section 5.8.1.2. The regression procedures and coefficient tests were then repeated using only the remaining non-outlier observations.

Another issue concerns the required regression assumption that residuals are uncorrelated and that the model is
correctly specified. The model may be misspecified, causing correlated residuals and biasing the results. To test for this, a test of model failure in the residuals was conducted for certain firm attributes. These attributes were chosen because previous research as shown that the return function may vary at different levels of firm capitalization (Banz, 1981; Reinganum, 1981). The size effect is not well understood on theoretical grounds. Firm asset size, growth, and sales level were therefore chosen as characteristics that may be components of any size effect. Further, firm structural characteristics (as reflected by balance sheet accounting data) may have different price functions at different growth and sales levels. Proxies for firm size, sales, and firm growth were therefore analyzed. This test is described in

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53This piecemeal approach was used because the dependent variable, abnormal returns adjusted for size, already provides a general control for overall market capitalization. The constituent components of size effects may not be fully controlled by methodologies that adjust for overall market capitalization. Price per share, for example, is related to stock returns (Stoll and Whaley, 1983; Blume and Stambaugh, 1983). The relationship is not fully explained by the notion that price per share is a simple proxy for market capitalization (Jaffe, Keim and Westerfield, 1990). One explanation for the valuation of stock price levels is that size and price per share are each proxies for more basic firm characteristics such as growth rate or volume level.

4For example, low levels of current assets, as a percentage of total assets, may be efficient at high volume levels where asset inflows and outflows are more diversified and less unbalanced. On the other hand, at high growth or low volume levels, this attribute may have a steeper pricing function because a larger buffer, or reservoir, of current assets and inventory may provide more efficiency.
section 5.8.1.3. Where residual analysis suggested that the model was misspecified for certain levels of size, growth, or sales, these observations were deleted and the regressions repeated for the remaining sub-set of original observations. Re-occurrence of the original results would then suggest that association shifts were not caused by model misspecification in these attributes.55

Similarly, return data are known to be correlated by industry, as discussed earlier. To correct for industry correlations, tests were conducted to detect industry dependency in the residuals. Where this dependency occurred and was detected, two different procedures were used to re-specify the model and control for industry effects. The dependency tests and regressions were then repeated for evidence that the univariate results were not driven by the effects of industry dependency. The industry tests and procedures are described in section 5.8.1.4.

55This problem is associated with the outlier problem. Model failure in a particular cross-sectional region of firm size, sales, or growth could generate high influence observations that disproportionately affect the resulting regression line. The coefficient values therefore may not be representative of what is occurring in the entire cross-section. They may instead be an artifact of model misspecification at certain levels of firm size, sales, or growth.
5.8.1.1 Tests for Multi-collinearity

The occurrence of multi-collinearity among variables in multiple regression can cause coefficient instability, thus confounding the interpretability of results.\(^6\) Collinearity can be the result of simple bi-variate correlation or it can take the form of more complex multiple dependencies involving three or more variables. To first check for evidence of bi-variate collinearity, a correlation matrix was produced and examined for high correlations.

Multiple dependency tests, in addition to checking for bi-variate dependencies, also explore the possibility that dependencies involve more than two variables. The eigenvalues and eigenvectors produced by a decomposition of the correlation matrix are useful in diagnosing multi-collinearity (Myers, 1990). One of the diagnostics derived from this decomposition is the condition number. The condition number is the ratio of the largest resulting eigenvalue to the smallest. An excessively large condition number indicates that the regression coefficients are unstable.\(^7\) In addition, the number of eigenvalues that are close to zero generally reflect

\(^6\)Prediction accuracy can also be affected in regions outside the space of the original data used to estimate a model (Myers, 1990).

\(^7\)A rule of thumb suggested in Myers (1990) is 1,000 for this diagnostic.
the number of collinearities in the data (Myers, 1990).

Another diagnostic tool derived from eigenvalue decomposition is variance inflation proportion analysis. When collinearity in a variable set exists, the variance of any coefficients involved is inflated. Variance inflation proportion analysis is designed to determine where coefficient variance inflation occurs for each collinear relationship associated with a particular near-zero eigenvalue. In effect, this tool can pinpoint which coefficients are most damaged by a given collinear relationship (Myers, 1990). This diagnostic also reflects the proportion of total variance inflation of a coefficient associated with each given eigenvalue. As such, by detecting high proportions of two or more variables on a given near-zero eigenvalue, the variables involved in a given dependency can be identified.

In this study the correlation matrix of each model, which included variables that passed the screens mentioned in section 5.8.1, was decomposed into its associated eigenvalues and eigenvectors. The condition number was computed and all near-zero eigenvalue identified. For these eigenvalues, the associated variance proportions were analyzed to detect the variables involved in any collinear dependencies. Variables were then deleted, where necessary, to improve collinear diagnostics and the interpretability of coefficient signs and magnitude.

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5.8.1.2 Outlier Detection and Deletion Procedures

In this study, "outliers" were detected and deleted in a manner similar to that used in Ou (1990). All observations with values in any of the tails of the independent variable distributions were deleted. The remaining observations were then re-tested in new regressions using the reduced dataset. This procedure, by partitioning the dataset into two groups defined by distance from a measure of central tendency, examines the cross-sectional robustness of any findings. Ou (1990) used a single standard deviation from the mean as her partition cutoff. There are problems associated with the use of that procedure in this study. First, accounting ratio distributions are known to be highly skewed in many cases. The mean is more sensitive than other measures of central tendency to this skewness. A benchmark cutoff whose value is mean-dependent is influenced towards less conservative values in highly skewed distributions. Further, any outliers can also affect the cutoff because they also directly affect the mean. Extreme outlier values would influence the cutoff towards a less conservative value. To correct these problems, firms were deleted according to percentile rank. The firms were ranked, for each accounting ratio, into twenty portfolios. If any observation appeared in the first or twentieth portfolio (representing the .05 and .95 distribution percentile) of any
accounting ratio, that observation was deleted. The use of percentile ranks is less sensitive to skewness because it essentially measures distance from the median center. The median is much less directly affected by outlier values.

5.8.1.3 Detection of Cross-Sectional Model Misspecification in Certain Firm Attributes

The procedures that tested for model failure, at certain levels of firm asset size, growth, and sales, were as follows. As stated earlier, model misspecification should result in higher residuals. Model failure is serious and can significantly impact the results if observation points are located in high leverage areas that can exert high influence on the resulting regression solution. To detect serious systematic failure, the data were divided into two groups: high influence observations and low influence observations. This was done using a measure of influence known as DFFITS (Myers, 1990). DFFITS measures the influence of any given observation point on the resulting regression line. It takes into account the leverage of an observation, as given from the corresponding diagonal of the regression HAT matrix (see Myers, 1990), and the degree of relative distance from the regression line, as represented by the studentized residuals. DFFITS is computed as follows:
\[ DFFITS_i = \frac{e_i}{s_i \sqrt{1-h_{ii}}} \sqrt{\frac{h_{ii}}{1-h_{ii}}}, \]

where \( e_i \) is the regression residual for the \( i \)th observation, \( h_{ii} \) is the HAT diagonal corresponding to the \( i \)th observation, and \( s_i \) is the standard deviation of the observation set with the \( i \)th observation deleted. When DFFITS is high for a given observation, this suggests that the data point is an outlier with sufficient leverage on the regression line to highly influence the resulting estimation. The appropriate benchmark point for DFFITS to be considered "highly influential" is suggested in Belsley, Kuh, and Welsch (1980). This is two times the square root of the fraction, \( p \) over \( n \), where \( n \) is the number of observations and \( p \) is the total number of parameters being estimated. Myers (1990) indicates that this value seems to work well in large data sets.

Using this benchmark, the original data were partitioned into two groups: high influence and the remaining data. Means for size, sales and firm growth were then computed for each group and tested for significant differences. If the means were significantly different, a cutoff point was established at the 90th and 10th percentile levels of the overall
distribution. Observations whose percentile ranking exceeded these values in the indicated direction were deleted. Regressions were then repeated to determine the robustness of any findings when the data are restricted to a narrower cross-sectional range.

5.8.1.4 Detection and Control of Residual Dependency Related To Industry Effects

A number of special problems have hampered researchers’ efforts to control for industry effects. Two types of codes are used to classify firms as to industry. These are the 4-digit SIC code as available in CRSP and the 4-digit DNUM code available in COMPUSTAT. These two codings are quite similar and involve progressively more specific industry classification as one moves from left to right through the 4 digits. Perhaps the most significant limitation in the use of these classifications is the large number of industry groups when three or more digits are used. Further, many companies are conglomerates, or are horizontally or vertically integrated, so that classification into any single industry group is difficult and often results in measurement error.

58A number of other cutoffs were tried. These did not seem to significantly modify the results. The 10th and 90th percentile cutoffs are the result of a trade-off between loss of sample and deletion of as many of the high influence observations as possible.
Perhaps the most straightforward way to test for industry effects is to add dummy variables for the industry code at whatever degree of specificity is feasible, given the loss of degrees of freedom, the resulting collinearity among variables, and overfitting concerns. This approach was used in Nerlove (1968). If the added variables add significantly to the explanatory power of the model, the notion that there is no industry dependency can be rejected.\(^9\) This test, while straightforward, cannot detect non-linear dependencies. It is also hampered by the degree of specificity that is possible. For example, at the three digit level, over 900 variables would be required.

In this study, two procedures to detect and control for industry dependencies were used. Using the first procedure, the observations were grouped by the first digit of the DNUM, so that seven dummy variables were required. The presence of industry effects was then tested with the following test:

\[
\frac{R(X,I) - R(X)}{\text{IND}} = \frac{7}{\text{MSE}},
\]

\(5.11\)

\(^9\)This is true, only to the point that limitations of specificity and misclassification risk, that were discussed earlier, do not confound this result.
where IND is a statistic distributed as F with degrees of freedom 7 and n-1, and n is the total number of observations. R is the total sums of squares of the model with regressors partitioned into X, the accounting ratio data, and I, the industry dummy variables described above. MSE is the mean square error for the full model.

The test described above, while having the advantage of allowing testing of the entire dataset, is limited because of the lack of industry specificity and sensitivity only to linear dependency. A second, more specific test is conducted on a partitioned subset of the overall data. In this test, the residuals from the original regression are partitioned into four quartile groups, from lowest to highest. A 4 by n contingency table is constructed, where n represents the number of industry groups, defined by the full 4-digit DNUM. Expected values for each cell are determined. If the residuals are uncorrelated with industry groups, a simple chi-square frequency test between the residual ranks and industry groups should be insignificant. For this test to be valid, the expected value of 80% of the table cells must be 5 or greater. To achieve this, all industry groups with less than 15 observations were deleted from these tests. This approach suffers from an important limitation. While permitting dependency testing at the 4-digit level and also checking for non-linear associations, the sub-set results may only be

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generalizable to industries with significant numbers of firm observations. This may exclude important business-cycle sensitive oligopolies (for example, automobile manufacturers and steel producers), as well as older, more capital intensive groups that may be more recession-sensitive.

If the Chi-Square test is significant, then dummy variables are created for all industry codes. The regression is repeated and results checked for consistency with previous findings. The dependency tests are also repeated to confirm that the added dummy variables, in a linear context, control for industry dependencies.

5.8.2 Procedures To Test Hypotheses (2a) and (2b)

5.8.2.1 The General Approach For Testing PDU Changes

Assume that a given set of accounting ratios is found to be associated only with the subsequent market-adjusted SARs of one BVCP type. Two possibilities exist. First, the associations may be sample-specific and coincidental. For example, other confounding events may be driving the associations. Second, the association of these accounting ratios with subsequent BVCP SARs may truly be affected by BVCP type.

Tests of hypotheses (2a) and (2b) provided further assurance that an interactive effect is occurring. The basic approach was to estimate models using previous BVCP data...
similar in type to the BVCP prediction period. The variables chosen for each of these models were those found in the univariate tests to be consistently sensitive to the BVCP type being estimated. These models were then used to predict returns in the two "holdout" BVCPs, each of which represented a different BVCP type. If the previous results were sample-specific or driven by confounding events, there should be no difference in predictive accuracy between models, regardless of which BVCP type was occurring. On the other hand, if predictive accuracy was greater when the holdout BVCP type matched that of the estimation BVCPs, this would support a rejection of hypotheses (1). This would also imply that PDU of these sets of accounting data vary across BVCP types.

5.8.2.2 Controls for Differences in Time-Dependence

Assume that differences in prediction accuracy are found that appear to be functions of BVCP type. What other design difficulties might account for the weakness? One possibility is that associations are degenerate across time. For example, one holdout prediction period may be located in closer proximity to the prediction period of the estimation BVCP.

\[60\] This assumes that the same confounding event is not re-occurring. Descriptive information on the event periods is provided later, in chapter 6, to assess the likelihood of this possibility.
proximity in time to the estimation periods of a given model.\textsuperscript{61} Any differences in predictive accuracy may therefore simply reflect the fact that one model was estimated with data more current than the other.

The procedures that were employed control for this possibility. First, consider the model estimated with the recession-sensitive variables of Table 10, Panel A, using previous recession-associated pooled BVCP data. For the case of the recession-associated holdout period (1981-1982), two "holdout" expansion-associated BVCPs exist surrounding this BVCP. The possibility of time-dependent results can be assessed by testing for differences in predictive accuracy using both the earlier expansion-associated BVCP (1974-1980) and the later one (1982-1987).\textsuperscript{62} If any differences are time-dependent, differences in prediction accuracy across BVCP type will vary depending on which expansion-associated BVCP is being used. Further, tests with the earlier expansion-associated BVCP will be biased conservatively. In this case, stronger prediction accuracy when estimation and prediction

\textsuperscript{61}Because the estimation periods are procyclical and mutually exclusive by definition, these proximity biases (which derive from differences in the periods of time being used for model estimation) will exist whenever other data non-stationarities cause systematic associations to be time-dependent.

\textsuperscript{62}Relative to the BVCP prediction interval (1981-1982).
BVCPs are similar would be strong evidence of an a BVCP type interaction.

Similarly in tests of the expansion-sensitive model and variables, for the case of the expansion-associated holdout period (1982-1987), two "holdout" recession-associated BVCPs exist (1973-1974 and 1981-1982). Each of these recession-associated BVCPs is closer in proximity to the expansion-associated estimation periods (1971 and 1975) than the similar expansion-associated holdout period. If greater predictive accuracy results when the holdout BVCP type matches that of the estimation periods, the evidence would be supportive because any time-dependency would discourage and bias the tests against significant findings.

5.8.2.3 Model Selection Procedures

First, the "best" prediction models described in section 5.8.1 were estimated. Both expansion-associated and recession-associated models were developed and estimated. As discussed in section 5.8.1, "best" models were selected using stepwise regression and the collinearity diagnostics discussed in section 5.8.1.1.
5.8.2.4 Model Estimation Procedures

After a best model was selected, the model parameters were estimated using pooled subsequent BVCP SAR data from the two least recent similar BVCP periods. As a result, data from the most recent BVCP period for each type were not used in estimating the models. These data were designated as holdout samples, and were reserved for the prediction tests of the estimated models.

Following estimation, predictions in the holdout periods were made using accounting ratios computed from data available immediately prior to each holdout BVCP period, as described earlier. Prediction errors were then computed for the estimated models by subtracting actual from predicted BVCP SARs. The prediction errors were then averaged cross-sectionally for each BVCP holdout period. The average prediction errors were then tested for significant differences across BVCPs and examined to determine which BVCP prediction was most accurate.

5.8.2.6 Controls and Tests for Model Misspecification, Outlier Effects and Industry Dependency

Because model misspecification can affect prediction accuracy, the procedures described in 5.1.1.2, 5.8.1.3 and 5.8.1.4 were re-applied, where practical, in the model
estimation procedures of section 5.8.2.5. These procedures deleted accounting ratio outlier observations to test for PDU in non-outlier regions of the cross-section. Similarly, firms with high growth and low sales were deleted to test for robustness of PDU results in the remaining subset of original data. Finally, industry control variables were added to detect any changes in predictive accuracy across BVCP type accounted for by industry misspecifications.
CHAPTER 6
RESULTS

6.1 INTRODUCTION

This chapter presents the results, and their interpretation, as related to the hypotheses stated in the previous chapter. The results are presented in two sections. First, the simple regression results are discussed in section 6.2. The variables that passed the criteria necessary to be considered in the multiple regression stage are also listed and discussed. Following the report of simple regression results, the multiple regression results are presented in section 6.3.

6.2 SIMPLE REGRESSION RESULTS

6.2.1 The Pooled Regression Results

The results of the first pass, pooled regressions, are listed in table 2 (located at the end of this section). Recession-associated and expansion-associated results are listed in juxtaposition to facilitate comparisons. All

RESULTS
associations significant at or below the .01 level of significance are shaded.

Twenty-three of the eighty-two accounting ratios were found to be significantly associated with pooled recession-associated BVCP SARs at the .01 level but not with similarly pooled expansion-associated SARs. On the other hand, just five of the eighty-two accounting-based ratio variables were found to be significantly associated (at the .01 level) with pooled expansion-associated BVCP SARs.

Four accounting-based ratio variables were significantly associated with SARs across both BVCP types. All of these variables show significant reversals in the sign of coefficients. Fifty variables (approximately 60%) were not significantly associated with any BVCP SARs in the pooled analysis.

Based on these findings, thirty-three variables show evidence of varying associations across BVCP type. These variables represent approximately 40% of all the accounting-based ratios tested. Further, every variable found to be significantly associated in any way with subsequent SARs also exhibited evidence of varying association across BVCP type. This evidence suggests that the null hypothesis (1) can be rejected for all variables that in simple regressions were significantly associated to subsequent SARs. In addition to this finding, the following specific results are of interest.

RESULTS
Many of the variables that are associated with recession-associated BVCP SARs are negatively signed. Those variables that are negatively associated include inventory/total assets, changes in inventory, sales and depreciation, changes in total assets and working capital, changes in leverage, issuance of long term debt, and changes in research and development. The negative associations found for these types of variables suggest that intractable and/or optimistic managements pursuing growth strategies experience the lowest SARs in subsequent recessionary cycles. For example, an optimistic management may take on debt and invest heavily in research and development, inventory and new assets. If recessionary conditions develop, these tactics become disadvantageous, thereby leading to lower recession-associated BVCP SARs. Accounting data may capture some of management’s intentions and tactics, increasing PDU to investors. Examining this behavioral notion is one possible extension of this study for future research.

Another result of interest is that many more variables are associated with subsequent recession-associated BVCP SARs than with expansion-associated BVCP SARs. This may be caused by the fact that recessionary conditions are sharper, more painful, and require more firm-specific actions in order to contend with them. Further research is needed to explore this and other possible causes for the different levels of RESULTS.
accounting data sensitivity that were detected across BVCP type.

A further result of interest concerns the variable associations that relate to profitability. In general, these variables (operating profit to sales, pre-tax income to sales, and net profit margin) are positively associated with recession-associated BVCP SARS and negatively associated with subsequent expansion-associated BVCP SARS. The magnitudes of association are fairly symmetric. This may imply that profitability measures capture a portion of systematic sensitivity to recession and expansion that estimates of beta and firm size do not. A more complete examination of the potential ability of some accounting-based profitability ratios to incrementally proxy for systematic risk sensitivity is still another possible extension of this research.\textsuperscript{63}

Finally, certain variables that relate to firm structure were significantly associated with subsequent BVCP SARS. For example, dividends to total assets were positively associated only with subsequent recession-associated BVCP SARS. High yielding stocks with low growth potential but steady income

\textsuperscript{63}The earnings to price ratio has been extensively examined by researchers in previous studies, as reported earlier in Chapter 4. In this study earnings to price is not consistently associated with subsequent BVCP SARS. On the other hand, other profitability measures that use accounting earnings do exhibit consistent associations. These have not been extensively examined by researchers as a proxy for systematic risk.
streams are widely believed by many in the investment community to be good defensive issues in recession-associated BVCPs. This research seems to confirm this. Another variable that was positively associated only with subsequent recession-associated BVCP SARs was cash relative to total assets. This measure of liquidity, combined with the positive associations of the current and quick ratios, implies that liquidity is priced by investors only in recession-associated BVCPs. Lastly, changes in firm leverage, as computed from a market value definition (total assets to market equity), seem to be important during both recession-associated and expansion-associated BVCPs. The direction of association reverses, however, as it did with the profitability measures, implying an incremental role for leverage changes in proxying for systematic risk sensitivity. On the other hand, changes in debt to equity, using historical cost measures of debt and equity, are insignificantly associated with subsequent BVCP SARs of any type. This may imply that historical cost based measures of leverage have less PDU to investors. This is another potential area of future research.
### TABLE 2
Simple Regression Results
(Pooled BVCP data)

<table>
<thead>
<tr>
<th>#</th>
<th>Acting Ratio Variable</th>
<th>N</th>
<th>$\beta_1$ (t)</th>
<th>N</th>
<th>$\beta_1$ (t)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Current ratio</td>
<td>2261</td>
<td>.0391 (5.85)</td>
<td>2332</td>
<td>-.0054 (-.72)</td>
</tr>
<tr>
<td>2</td>
<td>▲ in #1</td>
<td>2235</td>
<td>.0195 (.51)</td>
<td>2314</td>
<td>.1623 (2.86)</td>
</tr>
<tr>
<td>3</td>
<td>Quick Ratio</td>
<td>2085</td>
<td>.0517 (7.05)</td>
<td>2150</td>
<td>-.0112 (-1.38)</td>
</tr>
<tr>
<td>4</td>
<td>▲ in #3</td>
<td>2056</td>
<td>.0679 (2.18)</td>
<td>2131</td>
<td>.1382 (2.88)</td>
</tr>
<tr>
<td>5</td>
<td>Days Sales in Acct Rec</td>
<td>2107</td>
<td>-4.7430 (-.53)</td>
<td>2176</td>
<td>14.0829 (1.59)</td>
</tr>
<tr>
<td>6</td>
<td>▲ in #5</td>
<td>2072</td>
<td>.1003 (2.04)</td>
<td>2157</td>
<td>.0706 (2.32)</td>
</tr>
<tr>
<td>7</td>
<td>Inv turnover</td>
<td>1973</td>
<td>.0001 (.12)</td>
<td>2047</td>
<td>.0017 (1.10)</td>
</tr>
<tr>
<td>8</td>
<td>▲ in #7</td>
<td>1930</td>
<td>.2190 (3.64)</td>
<td>2015</td>
<td>-.0038 (-.05)</td>
</tr>
<tr>
<td>9</td>
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<td>2075</td>
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<td>$\beta_i$</td>
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<tr>
<td>20</td>
<td>#19, 1 yr lag</td>
<td>1815</td>
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<td>1990</td>
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<td>-.0068 (-.19)</td>
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<td>▲ in #27</td>
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<td>N: 2180, β₁: 0.0031 (0.33)</td>
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<td>Sales/total assets</td>
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<td>N: 1990, β₁: -0.0015 (-0.12)</td>
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<td>30</td>
<td>▲ in #29</td>
<td>N: 2302, β₁: 0.0006 (0.00)</td>
<td>N: 2421, β₁: 0.1199 (1.29)</td>
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<td>31</td>
<td>Return on total assets</td>
<td>N: 2169, β₁: 0.4927 (1.72)</td>
<td>N: 2259, β₁: 0.0454 (0.17)</td>
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<td>32</td>
<td>Ret on closing equity</td>
<td>N: 2347, β₁: -0.0185 (-0.10)</td>
<td>N: 2442, β₁: 0.0013 (0.01)</td>
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<td>33</td>
<td>Gross margin</td>
<td>N: 2137, β₁: 0.3692 (2.64)</td>
<td>N: 2216, β₁: -0.1428 (-1.08)</td>
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<td>34</td>
<td>▲ in #33</td>
<td>N: 2098, β₁: 0.0401 (0.75)</td>
<td>N: 2196, β₁: 0.0217 (0.49)</td>
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<td>Op profit to sales</td>
<td>N: 2297, β₁: 0.8493 (6.15)</td>
<td>N: 2388, β₁: -0.8082 (-6.26)</td>
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<td>▲ in #35</td>
<td>N: 2248, β₁: -0.0106 (-2.27)</td>
<td>N: 2358, β₁: -0.0084 (-0.70)</td>
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### TABLE 2
Simple Regression Results
(Pooled BVCP data)

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<tr>
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<th>Recession-Associated N</th>
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<th>Expansion-Associated N</th>
<th>$\beta_1$ (t)</th>
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<tr>
<td>37</td>
<td>Pretax income to sales</td>
<td>2349 1.3050 (7.96)</td>
<td>2446 -.2434 (-3.99)</td>
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<td>38</td>
<td>▲ in #37</td>
<td>2304 .0056 (.82)</td>
<td>2420 -.0142 (-1.83)</td>
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<td>39</td>
<td>Net profit margin</td>
<td>2168 1.6486 (8.36)</td>
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<td>40</td>
<td>▲ in #39</td>
<td>2086 -.0038 (-2.58)</td>
<td>2194 -.0171 (-2.09)</td>
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<td>41</td>
<td>Sales to total cash</td>
<td>2178 -.0004 (-1.69)</td>
<td>2265 .0001 (.39)</td>
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<td>Sales to accts rec</td>
<td>2107 .0001 (.14)</td>
<td>2176 .0000 (.09)</td>
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<td>43</td>
<td>Sales to inv</td>
<td>2002 .0000 (.03)</td>
<td>2074 .0020 (1.79)</td>
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<td>1973 .1465 (2.65)</td>
<td>2047 .0660 (1.91)</td>
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<td>45</td>
<td>Sales to working capital</td>
<td>1805 -.0070 (-.46)</td>
<td>1869 -.0452 (-3.22)</td>
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## TABLE 2
**Simple Regression Results**
(Pooled BVCP data)

<table>
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<th>Expansion-Associated</th>
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<td>1852</td>
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<td>.1699 (2.48)</td>
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<td>2405</td>
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<td>.0000 (.03)</td>
<td>.0000 (.16)</td>
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<td>2386</td>
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<td>.0053 (.86)</td>
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<td>-.2313 (2.85)</td>
<td>-.0219 (-.55)</td>
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<tr>
<td>50</td>
<td>▲ in R&amp;D to sales</td>
<td>552</td>
<td>637</td>
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<td>-.1799 (-1.76)</td>
<td>-.0131 (-.29)</td>
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<td>572</td>
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<td>-.1313 (-.43)</td>
<td>-.0231 (-.72)</td>
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<td>52</td>
<td>▲ in adv to sales</td>
<td>241</td>
<td>572</td>
</tr>
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<td>.2330 (.22)</td>
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<td>2422</td>
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<td>939</td>
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<td>-.2848 (-.34)</td>
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<tr>
<td>#</td>
<td>Acting Ratio Variable</td>
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<td>Expansion-Associated</td>
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<td>.0747 (.35)</td>
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<td>▲ in #57</td>
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<td>-.0088 (-.61)</td>
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<td>Repay of LT debt (%)</td>
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<td>Issuance of LT debt (%)</td>
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<td>63</td>
<td>Purchase of tr stock</td>
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### TABLE 2
Simple Regression Results
(Pooled BVCP data)

<table>
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<tr>
<th>#</th>
<th>Acting Ratio Variable</th>
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<td>Cash div (%)</td>
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<td>-0.0050 (-2.09)</td>
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<td>69</td>
<td>Tot assets to mk eq</td>
<td>2336</td>
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<td>-0.2404 (-5.15)</td>
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<td>855</td>
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<td>Expansion-Associated</td>
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<td>▲ in #75</td>
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<td>.1303 (1.26)</td>
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6.2.2 The Unpooled Regression Results

The results of the previous sub-section suggest that associations of accounting-based ratio data with BVCP SARs vary across BVCP type. Nevertheless, the evidence is not conclusive. Because business cycle events are clustered by definition, it is possible that the effects observed are caused by exogenous confounding events that are not controlled. Any associations could therefore be sample specific.

To test for this possibility variables that were significantly associated with BVCP SARs in the pooled regressions are used again in sub-period unpooled regressions. If the association observed is truly a function of BVCP type, it should be observed within all similar BVCP subperiods. On the other hand, if subperiod results are not consistent, either because of conflicting findings of association, or insignificance in one or more similar sub-periods, this would suggest that the original pooled findings are suspect and could have been a sample-specific result.

6.2.2.1 Descriptive Comparisons of BVCP Measurement Intervals

One caveat remains in this indirect approach to detecting the presence of confounding events. If a confounding event repeats across BVCPs, then evidence of consistent
associations across BVCP type may still be a function of the repeating confounding event. BVCP measurement intervals in this study are spaced out over thirteen years. The possibility of an event of this duration is therefore somewhat remote. Nevertheless, BVCP measurement intervals were examined for confounding events such as inflation conditions, states of war or peace, interest rate levels, the shape of the yield curve, risk premia levels, exchange rates, trade deficits, and changes in the size of the federal deficit. Table 3 which follows lists these possible confounding events, the proxy measure for each and the value of the proxy.

Interest rates vary across the various intervals from a low of 5.68% to a high of 11.37%. The periods encompassed a period of escalating wartime tensions, de-escalation, and peace. The money supply changed at various rates from a low of 3.8% to a high of 12.9%. Inflation, as measured by changes in the CPI index, increased throughout the BVCP measurement intervals from a low of 4.1% to a high of 13.4%. Changes in federal deficits gradually increased. Risk premia varied throughout the periods. 64 None of these possible confounding

64Risk premia refers to the premia attached to various bonds as a function of their potential default risk. It is often measured for a specific issue as the difference in effective yield between a given bond issue and a U.S. government bond that has the same maturity length. This amounts to assuming that the government issue is risk-free. Therefore, given a world of rational pricing, any excess yield over that of a government bond is the price investors demand to bear the additional risk of default.
events varied systematically across BVCP type. The only exception was the yield curve, which was systematically higher in expansion-associated BVCP measurement intervals. While this may have affected some accounting ratios related to debt and debt costs, the yield curve differences may be explained by federal reserve interventions that helped precipitate expansion and recession. Therefore, the yield curve may covary with business cycle related BVCPs because it is implicitly associated with the underlying recession and expansion events.
### Table 3
Descriptive Statistics of BVCP Measurement Intervals

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<tr>
<th>Int</th>
<th>Beginning Date</th>
<th>Int Rate*</th>
<th>War/peace</th>
<th>△ in M1</th>
<th>△ in CPI</th>
<th>△ in Fed def</th>
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<td>r'</td>
<td>12/68</td>
<td>6.86</td>
<td>War</td>
<td>.038</td>
<td>.059</td>
<td>.003</td>
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<tr>
<td>e_1</td>
<td>5/70</td>
<td>5.68</td>
<td>War</td>
<td>.064</td>
<td>.041</td>
<td>.026</td>
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<td>r_2</td>
<td>1/73</td>
<td>7.20</td>
<td>Peace</td>
<td>.054</td>
<td>.062</td>
<td>.033</td>
</tr>
<tr>
<td>e_2</td>
<td>10/74</td>
<td>6.57</td>
<td>Peace</td>
<td>.053</td>
<td>.079</td>
<td>.074</td>
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<td>r_3</td>
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<td>11.37</td>
<td>Peace</td>
<td>.067</td>
<td>.134</td>
<td>.071</td>
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<td>e_3</td>
<td>8/82</td>
<td>9.70</td>
<td>Peace</td>
<td>.129</td>
<td>.024</td>
<td>.159</td>
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<table>
<thead>
<tr>
<th>Int</th>
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<th>Risk Pr**</th>
<th>Yield curve#</th>
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<tr>
<td>r'</td>
<td>12/68</td>
<td>416</td>
<td>.007</td>
<td>.000</td>
</tr>
<tr>
<td>e_1</td>
<td>5/70</td>
<td>762</td>
<td>.011</td>
<td>.046</td>
</tr>
<tr>
<td>r_2</td>
<td>1/73</td>
<td>7140</td>
<td>.008</td>
<td>-.090</td>
</tr>
<tr>
<td>e_2</td>
<td>10/74</td>
<td>14077</td>
<td>.014</td>
<td>.010</td>
</tr>
<tr>
<td>r_3</td>
<td>1/80</td>
<td>1898</td>
<td>.017</td>
<td>.000</td>
</tr>
<tr>
<td>e_3</td>
<td>8/82</td>
<td>-20412</td>
<td>.018</td>
<td>.021</td>
</tr>
</tbody>
</table>

*proxied by 6-month t-bill rate.
^Includes imports, exports, investment receipts and payments, military transactions, travel, services and misc. transfers (Source: Economic Statistics, 1900-1983)
**proxied by spread between Aaa and Baa seasoned corporate bonds
#proxied by spread between 30yr and 1yr government bonds. When only yearly data was available, values were computed using weighted averages.
6.2.2.2 Table Description of UnPooled Results

The unpoled results for variables that were significantly associated with recession-associated BVCP SARs in the pooled tests are presented in Table 4. The first two columns present coefficient estimates and t statistics for the two similar recession-associated BVCPs. The last two columns contain the same statistics for the two expansion-associated BVCPs.

Table 5 contains the results for variables that were significantly associated with expansion-associated BVCP SCARs in the pooled tests. Again, the results of each BVCP subperiod are presented in juxtaposition, with similar BVCPs listed first.

All associations significant at or below the .05 level of significance are shaded. The .05 level is used in all unpoled tests that follow, in consideration of the lower number of observations in the unpoled BVCP tests. Only variables with data available across all BVCPs are presented in Tables 4 and 5. Tables 4 and 5 appear at the end of this sub-section.
6.2.2.3 Interpretation Of Unpooled Results: Recession-Associated

An examination of Table 4 reveals that of the 25 accounting-based ratios that were significantly associated with recession-associated BVCP SARS, fourteen were consistently associated with BVCP SARS across both similar recession-associated BVCP sub-periods. Two of these fourteen ratios, change in total assets and the current ratio, are also significantly associated in the same direction with at least one expansion-associated BVCP. The remaining twelve variables' associations to subsequent BVCP SARS consistently vary across BVCP type for all BVCP sub-periods. The twelve variables that showed these consistent results were: (1) quick ratio, (2) change in inventory, (3) change in sales, (4) change in depreciation, (5) operating profit to sales, (6) pre-tax income to sales, (7) net profit margin, (8) change in working capital, (9) change in total assets to market equity (10) change in retained earnings/total assets, (11) dividends to total assets, and (12) cash to total assets. This suggests that rejection of hypothesis (1) is indicated for this sub-set of the original variables under study.
6.2.2.4 Interpretation Of Unpooled Results: Expansion-Associated

An examination of Table 5 reveals that of the nine variables that were significantly associated with pooled SCARs from expansion-associated BVCPs, five variables could be confirmed as demonstrating consistent results across the expansion-associated BVCP subperiods. These were: (1) depreciation/plant assets; (2) operating profit to sales; (3) pre-tax income to sales; (4) net profit margin; and (5) change in total assets to market equity. All of these variables exhibited consistent variation in association across BVCP type for all BVCP sub-periods tested. As with the evidence for recession-associated BVCP associations, this suggests that confounding events do not account for the results in the pooled tests and hypothesis (1) can be rejected for this subset of accounting-based ratios.
<table>
<thead>
<tr>
<th>#</th>
<th>Accting Ratio</th>
<th>Recession-Associated</th>
<th>Expansion-Associated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$\beta_1$ (t)</td>
<td>$\beta_1$ (t)</td>
</tr>
<tr>
<td>1</td>
<td>Current ratio</td>
<td>.0353 (1.92)</td>
<td>.0396 (5.43)</td>
</tr>
<tr>
<td>3</td>
<td>Quick ratio</td>
<td>.0511 (2.14)</td>
<td>.0518 (6.64)</td>
</tr>
<tr>
<td>8</td>
<td>▲ in inv t-over</td>
<td>-.0019 (-.01)</td>
<td>.3025 (4.25)</td>
</tr>
<tr>
<td>9</td>
<td>Inv/total assets</td>
<td>-.1877 (-.83)</td>
<td>-1.4534 (-7.41)</td>
</tr>
<tr>
<td>11</td>
<td>▲ in inv</td>
<td>-.0388 (-2.27)</td>
<td>-.4377 (-6.08)</td>
</tr>
<tr>
<td>12</td>
<td>▲ in sales</td>
<td>-.2533 (-4.51)</td>
<td>-.3765 (-3.69)</td>
</tr>
<tr>
<td>13</td>
<td>▲ in dep</td>
<td>-.1110 (-2.28)</td>
<td>-.5211 (-6.18)</td>
</tr>
</tbody>
</table>
**TABLE 4**

**Simple Regression Results**

**Significant Recession-Associated Accounting Ratios**

*(Unpooled BVCP data)*

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>17</td>
<td>Oper ret on equity</td>
<td>-.0593 (-.72)</td>
<td>-.5582 (-4.01)</td>
<td>.3309 (1.71)</td>
<td>.3353 (-1.92)</td>
</tr>
<tr>
<td>33</td>
<td>Gross margin</td>
<td>1.2320 (5.70)</td>
<td>-.1641 (-.90)</td>
<td>.4178 (2.08)</td>
<td>-.5210 (-3.00)</td>
</tr>
<tr>
<td>35</td>
<td>Oper profit/sales</td>
<td>.7527 (3.51)</td>
<td>.9113 (5.03)</td>
<td>-.5197 (-2.63)</td>
<td>-1.0251 (-6.00)</td>
</tr>
<tr>
<td>37</td>
<td>Pre-tax inc to sales</td>
<td>1.6583 (6.16)</td>
<td>1.1203 (5.38)</td>
<td>-.5391 (-3.07)</td>
<td>-.2030 (-3.11)</td>
</tr>
<tr>
<td>39</td>
<td>Net profit margin</td>
<td>1.7167 (4.76)</td>
<td>1.6205 (6.83)</td>
<td>-.5981 (-2.94)</td>
<td>-.1836 (-2.78)</td>
</tr>
<tr>
<td>40</td>
<td>▲ in #39</td>
<td>.0454 (1.95)</td>
<td>-.0040 (-2.64)</td>
<td>-.0213 (-1.64)</td>
<td>-.0139 (-1.31)</td>
</tr>
<tr>
<td>44</td>
<td>▲ in sales/ inv</td>
<td>.0470 (.62)</td>
<td>.2859 (3.25)</td>
<td>.0409 (1.13)</td>
<td>.2133 (2.30)</td>
</tr>
</tbody>
</table>

**RESULTS**
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>( \beta_1 ) (t)</td>
<td>( \beta_1 ) (t)</td>
<td>( \beta_1 ) (t)</td>
<td>( \beta_1 ) (t)</td>
</tr>
<tr>
<td>53</td>
<td>( \Delta ) in total assets</td>
<td>-.3954 (-5.58)</td>
<td>-.9071 (-6.90)</td>
<td>.1171 (2.16)</td>
<td>-.4011 (-2.73)</td>
</tr>
<tr>
<td>55</td>
<td>w cap/total assets</td>
<td>.0024 (.04)</td>
<td>.1630 (6.46)</td>
<td>*p1580x.1746 -.0488</td>
<td></td>
</tr>
<tr>
<td>57</td>
<td>Oper inc/ t assets</td>
<td>-.2319 (-.89)</td>
<td>-1.5873 (-7.77)</td>
<td>-.6426 (-2.92)</td>
<td>.4592 (2.37)</td>
</tr>
<tr>
<td>67</td>
<td>( \Delta ) in work cap</td>
<td>-.2638 (-4.04)</td>
<td>-.3392 (-3.24)</td>
<td>.1148 (1.81)</td>
<td>-.0759 (-.67)</td>
</tr>
<tr>
<td>69</td>
<td>Tot assets to m eq</td>
<td>-10.2574 (.80)</td>
<td>40.9299 (4.53)</td>
<td>-36.4354 (-2.64)</td>
<td>1.1715 (.31)</td>
</tr>
<tr>
<td>70</td>
<td>( \Delta ) in #69</td>
<td>-.2181 (-2.54)</td>
<td>-.2939 (-4.85)</td>
<td>.0989 (2.86)</td>
<td>.0698 (2.94)</td>
</tr>
<tr>
<td>72</td>
<td>( \Delta ) in T assets to bk v</td>
<td>-.1622 (-1.13)</td>
<td>-.1934 (-2.36)</td>
<td>-.0023 (-.01)</td>
<td>.0784 (.34)</td>
</tr>
</tbody>
</table>
### TABLE 4
Simple Regression Results
Significant Recession-Associated Accounting Ratios
(Unpooled BVCP data)

<table>
<thead>
<tr>
<th>#</th>
<th>Accting Ratio</th>
<th>Recession-Associated</th>
<th>Expansion-Associated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$\beta_1$ (t)</td>
<td>$\beta_1$ (t)</td>
</tr>
<tr>
<td>73</td>
<td>Bk to mk equity</td>
<td>141.2650 (1.39)</td>
<td>155.4192 (4.20)</td>
</tr>
<tr>
<td>78</td>
<td>△ in r earn/ t assets</td>
<td>.6511 (3.65)</td>
<td>1.1653 (5.53)</td>
</tr>
<tr>
<td>79</td>
<td>Div to total assets</td>
<td>6.0259 (5.17)</td>
<td>1.0844 (2.83)</td>
</tr>
<tr>
<td>81</td>
<td>Cash to tot assets</td>
<td>.6039 (1.70)</td>
<td>1.1497 (3.82)</td>
</tr>
<tr>
<td>----</td>
<td>--------------</td>
<td>----------------</td>
<td>----------------</td>
</tr>
<tr>
<td>2</td>
<td>$\Delta$ in current ratio</td>
<td>.2067 (2.82)</td>
<td>.0971 (1.08)</td>
</tr>
<tr>
<td>4</td>
<td>$\Delta$ in quick ratio</td>
<td>.1363 (2.20)</td>
<td>.1386 (1.84)</td>
</tr>
<tr>
<td>15</td>
<td>Dep/plant assets</td>
<td>2.5476 (5.04)</td>
<td>.8979 (2.29)</td>
</tr>
<tr>
<td>35</td>
<td>Oper profit/sales</td>
<td>-.5197 (-2.63)</td>
<td>-1.0251 (-6.00)</td>
</tr>
<tr>
<td>37</td>
<td>Pre-tax inc to sales</td>
<td>-.5391 (-3.07)</td>
<td>-.2030 (-3.11)</td>
</tr>
<tr>
<td>39</td>
<td>Net profit margin</td>
<td>-.5981 (-2.94)</td>
<td>-.1836 (-2.78)</td>
</tr>
<tr>
<td>45</td>
<td>Sales to work capital</td>
<td>-.0720 (-3.43)</td>
<td>-.0253 (-1.34)</td>
</tr>
</tbody>
</table>
### TABLE 5

**Simple Regression Results**  
**Significant Expansion-Associated Accounting Ratios**  
(Unpooled BVCP data)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>β₁ (t)</td>
<td>β₁ (t)</td>
<td>β₁ (t)</td>
<td>β₁ (t)</td>
</tr>
<tr>
<td>70</td>
<td>Δ in t assets to m eq</td>
<td>.0989 (2.86)</td>
<td>.0698 (2.94)</td>
<td>-.2181 (-2.54)</td>
<td>-.2939 (-4.85)</td>
</tr>
<tr>
<td>77</td>
<td>Ret earn/t assets</td>
<td>-.4487 (-2.58)</td>
<td>.0741 (.44)</td>
<td>.6511 (3.65)</td>
<td>1.1653 (5.53)</td>
</tr>
</tbody>
</table>

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6.2.3 The Transformation Results

As mentioned earlier, transformations were conducted by first transforming the eighty-two accounting ratios and then regressing the transformed variables onto SARs pooled by BVCP type. To permit more concise reporting, only the results of uniquely significant associations are reported. Tables are presented in similar format to previous pooled BVCP results. The transformations are analyzed to first test hypothesis (1) for the transformed variables. Then significantly associated variables are tested with unpooled data for consistent association within BVCP type. Finally, the robustness, direction and strength of associations are analyzed as criteria for inclusion in the multiple regression tests. In this part of the analysis, significant associations are compared across transformations to see if the strength of association was improved by the transformation.

6.2.3.1 The Results of Log and Square Root Transformations

The results of the log and square root transformations produced only one uniquely significant association with subsequent BVCP SARs pooled by BVCP type.65 This association was found for the sales/total assets ratio (#29). For both

---

65Unique relative to the results using untransformed variables.
transformations, this variable was consistently associated only to subsequent expansion-associated BVCP SARs. Similarly, no simple regressions show increased adjusted $r^2$ in the regressions that used log and square root transformations of accounting ratios. This result indicates that log and square root transformations do not substantively increase the PDU of accounting data, at least in the simple regression context, in predicting subsequent BVCP SARs.

6.2.3.2 The Results of Higher Order Transformations

The higher order transformations are examined because the non-linear behavior of ratios described earlier may be better modeled by higher order terms. In the tests made in this study, accounting ratios were squared and cubed. The resulting transformations were then regressed onto subsequent pooled BVCP SARs. Any uniquely associated variables were further tested with the unpooled procedures used earlier.

66The pooled regression results, using expansion associated BVCP data were: coefficient of 921.77 and adjusted $R^2$ of .003 for the log transformation; and coefficient of 14.01 and adjusted $R^2$ of .005 for the square root transform.

The Log transformation coefficients for the 1971-1973 and 1974-1980 BVCP sub-periods were 890.72 and 598.63, with adjusted $R^2$ of .007 and .003, respectively. Both regressions were significant at the .05 level.

The square root transformations for this variable using data from the same respective BVCP sub-periods, produced significant coefficients of 17.81 and 11.97 with Adjusted $R^2$ of .007 and .003.
The square transformations produced two uniquely significant associations to subsequent pooled expansion-associated BVCP SARs: Change in days sales to accounts receivable (#6); and change in working capital to total assets (#56). Change in sales to accounts receivable was significant for regressions using pooled, expansion-associated, BVCP data and insignificant otherwise. In the unpoled tests however, this variable was significant in only one of the two sub-periods (the expansion-associated BVCP from 1971-1973).

When expansion-associated pooled BVCP data were regressed on subsequent SARs, the coefficient value for change in working capital to total assets (#56) was significant at the .01 level. The regression for the same transformed variable, using recession-associated BVCP data, was insignificant. Further, this variable was consistently significantly associated with subsequent expansion-associated BVCP SARs in the unpoled tests (coefficients of .0048 and .3463 for the two BVCP expansion-associated sub-periods were both significant at the .05 level). Adjusted $r^2$ in the regression using pooled expansion-associated data was .004. There were no unique associations to recession-associated pooled BVCP SARs.

The cubed transformations produced no new uniquely associated ratio variables, with the exception of change in days sales to accounts receivable (#6). The results for this
variable were similar to the squared transformation. This transformed accounting ratio was uniquely associated to expansion-associated pooled BVCP SARs but the result was not found to be robust in all expansion-associated unpooled BVCPs.\footnote{The coefficient for 1971-1973 expansion-associated BVCP was .000160 and was significant at the .05 level. The regression using 1974-1980 expansion-associated BVCP data was insignificant. Neither recession-associated BVCP regression was significant for this transformed variable. The adjusted $R^2$ for the one significant sub-period was .006.}

No simple regressions showed increased adjusted $r^2$ in the regressions that used square and cubed transformations of accounting ratios. Most were insignificantly associated at the .01 level. This result indicates that square and cube transformations do not increase the PDU of accounting data, at least in the univariate context, in predicting subsequent BVCP SARs. This result is consistent with previous research on the return associations of squared terms (Altman, 1970; O’Connor, 1973).

6.2.3.3 The Results of Regressions Using Standardized Variables

Variables adjusted for location and standardized by the BVCP standard deviation, thus creating scale-free variables, showed only two uniquely significant accounting ratio

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associations with subsequent BVCP SARs (relative to the untransformed results). These two variables were sales/total assets and sales/working capital. Sales/total assets was significantly associated with pooled and unpooled SARs from expansion-associated BVCPs. Sales/working capital was significantly associated with pooled SARs from recession-associated BVCPs. The result for sales to working capital, however, was not robust nor consistent in the sub-period tests. This variable was significantly associated with SARs in only one of the two recession-associated BVCPs. The general lack of unique results using standardizing transformations suggests that variable location and dispersion shifts across BVCPs are not a major factor in the reported simple regression results.

On the other hand, several accounting ratio variables demonstrated stronger magnitudes of association when ratio observations were standardized prior to pooling. These are reported, together with the rank results in Table 9 at the end of this sub-section.

6.2.3.4 Rank Transformation Results with Pooled BVCP Data

Table 6 reports the results of regressions of BVCP SARs, pooled by BVCP type, on accounting ratio variables transformed into ranks as described earlier. The rank transformations yielded twenty new significantly associated ratios. Of these, results
twelve were significant with pooled recession-associated BVCP SCARs but not with expansion-associated BVCP SARs. Six rank-transformed accounting-based ratios were uniquely associated only to expansion-associated BVCPs in the pooled tests. Two others were significantly associated across both types of BVCPs but exhibited sign reversal across BVCP type. This suggests that hypothesis (1) can be rejected for twenty three additional rank-transformed accounting ratios.
### TABLE 6
Simple Regression Results
Uniquely Significant Rank-Transformed Accounting Ratios
(Pooled BVCP data)

<table>
<thead>
<tr>
<th>#</th>
<th>Acting Variable</th>
<th>N</th>
<th>β₁</th>
<th>N</th>
<th>β₁</th>
</tr>
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<td></td>
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<td>(t)</td>
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<td>(t)</td>
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<td>1</td>
<td>Current</td>
<td>1660</td>
<td>.1195</td>
<td>1660</td>
<td>.2687</td>
</tr>
<tr>
<td></td>
<td>ratio</td>
<td></td>
<td>(1.48)</td>
<td></td>
<td>(3.49)</td>
</tr>
<tr>
<td>10</td>
<td>△ in inv/ tot</td>
<td>1439</td>
<td>-.2882</td>
<td>1453</td>
<td>-.1204</td>
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<td>assets</td>
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<td>(-1.46)</td>
</tr>
<tr>
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<td>1671</td>
<td>.5616</td>
</tr>
<tr>
<td></td>
<td>assets</td>
<td></td>
<td>(-2.92)</td>
<td></td>
<td>(7.46)</td>
</tr>
<tr>
<td>18</td>
<td>△ in ret on</td>
<td>1650</td>
<td>.2519</td>
<td>1682</td>
<td>-.1866</td>
</tr>
<tr>
<td></td>
<td>oper equity</td>
<td></td>
<td>(3.14)</td>
<td></td>
<td>(-2.45)</td>
</tr>
<tr>
<td>21</td>
<td>Debt to</td>
<td>1305</td>
<td>-.3521</td>
<td>1682</td>
<td>-.1866</td>
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<tr>
<td></td>
<td>equity</td>
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<td></td>
<td>(-2.45)</td>
</tr>
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<td>(-.66)</td>
<td></td>
<td>(-3.73)</td>
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<td>1548</td>
<td>-.2222</td>
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<tr>
<td></td>
<td>debt to equity</td>
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<td>.3348</td>
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<tr>
<td></td>
<td>assets</td>
<td></td>
<td>(-.18)</td>
<td></td>
<td>(4.43)</td>
</tr>
<tr>
<td>28</td>
<td>△ in tm interest earned</td>
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<td>.2702</td>
<td>1554</td>
<td>.0603</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>(3.40)</td>
<td></td>
<td>(.76)</td>
</tr>
</tbody>
</table>
### TABLE 6
Simple Regression Results
Uniquely Significant Rank-Transformed Accounting Ratios
(Pooled BVCP data)

<table>
<thead>
<tr>
<th>#</th>
<th>Acting Ratio Variable</th>
<th>N</th>
<th>$\beta_1$ (t)</th>
<th>N</th>
<th>$\beta_1$ (t)</th>
</tr>
</thead>
<tbody>
<tr>
<td>29</td>
<td>Sales/total assets</td>
<td>1690</td>
<td>-0.4345 (-5.50)</td>
<td>1699</td>
<td>0.4138 (5.49)</td>
</tr>
<tr>
<td>30</td>
<td>$\Delta$ in sales/t assets</td>
<td>1675</td>
<td>0.2132 (2.67)</td>
<td>1695</td>
<td>0.0077 (.10)</td>
</tr>
<tr>
<td>34</td>
<td>$\Delta$ in gross margin</td>
<td>1506</td>
<td>0.2153 (2.44)</td>
<td>1523</td>
<td>-0.2335 (-2.92)</td>
</tr>
<tr>
<td>36</td>
<td>$\Delta$ in oper pr to sales</td>
<td>1646</td>
<td>0.3213 (3.98)</td>
<td>1671</td>
<td>0.0078 (.10)</td>
</tr>
<tr>
<td>38</td>
<td>$\Delta$ in p-tax inc to sales</td>
<td>1676</td>
<td>0.3589 (4.51)</td>
<td>1695</td>
<td>0.0639 (.84)</td>
</tr>
<tr>
<td>41</td>
<td>Sales to total cash</td>
<td>1535</td>
<td>-0.4707 (-5.45)</td>
<td>1543</td>
<td>0.0244 (.30)</td>
</tr>
<tr>
<td>47</td>
<td>Sales to fixed assets</td>
<td>1682</td>
<td>-0.3819 (-4.85)</td>
<td>1691</td>
<td>0.4602 (6.13)</td>
</tr>
<tr>
<td>48</td>
<td>$\Delta$ in prod</td>
<td>1670</td>
<td>0.2140 (2.69)</td>
<td>1687</td>
<td>-0.0729 (-.96)</td>
</tr>
<tr>
<td>55</td>
<td>Working cap/tot assets</td>
<td>1282</td>
<td>0.1105 (1.17)</td>
<td>1285</td>
<td>0.2731 (3.15)</td>
</tr>
<tr>
<td>#</td>
<td>Accting Ratio Variable</td>
<td>N</td>
<td>$b_1$</td>
<td>N</td>
<td>$b_1$</td>
</tr>
<tr>
<td>----</td>
<td>--------------------------------</td>
<td>-----</td>
<td>--------</td>
<td>-----</td>
<td>--------</td>
</tr>
<tr>
<td>58</td>
<td>▲ in op inc/ t assets</td>
<td>1076</td>
<td>-.4117</td>
<td>1085</td>
<td>-.1292</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-3.94)</td>
<td></td>
<td>(-1.36)</td>
</tr>
<tr>
<td>59</td>
<td>▲ in uses of funds</td>
<td>749</td>
<td>-.0188</td>
<td>753</td>
<td>-.2992</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-.14)</td>
<td></td>
<td>(-2.58)</td>
</tr>
<tr>
<td>65</td>
<td>▲ in LT debt</td>
<td>1504</td>
<td>-.2632</td>
<td>1549</td>
<td>-.1875</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-3.27)</td>
<td></td>
<td>(-2.37)</td>
</tr>
<tr>
<td>66</td>
<td>Cash div as % of csh flow</td>
<td>754</td>
<td>.0972</td>
<td>757</td>
<td>-.3368</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(.75)</td>
<td></td>
<td>(-2.90)</td>
</tr>
<tr>
<td>68</td>
<td>Net inc/ cash flows</td>
<td>754</td>
<td>-.5194</td>
<td>757</td>
<td>.0983</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-4.10)</td>
<td></td>
<td>(.84)</td>
</tr>
</tbody>
</table>

Note: Shaded areas represent regressions that were significant at the .01 level.
6.2.3.5 Rank Transformation Results Using Unpooled BVCP Data: The Recession-associated Results

To further test hypothesis (1) and determine robustness of the results within BVCP type, the regressions were repeated using unpooled data, in a manner similar to the methodology used in the untransformed case. The results for variables significant with pooled recession-associated BVCP SARS are reported in Table 7. The results for variables significant with pooled expansion-associated BVCP SARS are reported in Table 8.

In Table 7 five of the fourteen accounting ratio variables that were significantly associated with recession-associated pooled subsequent BVCP SCARs continue to be significantly associated in all unpooled recession-associated BVCPs. All of these exhibit variation in association across BVCP type for all BVCP subperiods. These variables are: (1) depreciation/ plant assets; (2) change in times interest earned; (3) change in operating profit to sales; (4) change in pre-tax income to sales; and (5) change in long term debt. These variables are similar to those found significant in the untransformed case in that they track debt changes, growth of assets, and profitability. They differ, however, in that many of these involve first difference percentage changes in accounts.
TABLE 7
Simple Regression Results
Significant Recession-Associated Accounting Ratios
Uniquely Associated Rank-Transformed Variables
(Unpooled BVCP data)

<table>
<thead>
<tr>
<th>#</th>
<th>Accting Ratio</th>
<th>$r_1$ (t)</th>
<th>$r_2$ (t)</th>
<th>$e_1$ (t)</th>
<th>$e_2$ (t)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>▲ in inv/ t assets</td>
<td>-.1875 (-1.56)</td>
<td>-.3780 (-3.50)</td>
<td>-.1937 (-1.83)</td>
<td>-.2138 (-2.01)</td>
</tr>
<tr>
<td>15</td>
<td>Dep/ plant assets</td>
<td>-.2801 (-2.57)</td>
<td>-.2009 (-2.03)</td>
<td>.5908 (5.89)</td>
<td>.3050 (3.18)</td>
</tr>
<tr>
<td>18</td>
<td>▲ in ret on open eq</td>
<td>.1142 (1.16)</td>
<td>.3407 (3.49)</td>
<td>-.2611 (-2.61)</td>
<td>-.0374 (-.40)</td>
</tr>
<tr>
<td>21</td>
<td>Debt to equity</td>
<td>-.6317 (-4.68)</td>
<td>-.0509 (-.44)</td>
<td>-.1926 (-1.60)</td>
<td>.0897 (.83)</td>
</tr>
<tr>
<td>28</td>
<td>▲ in tme int earned</td>
<td>.2983 (2.72)</td>
<td>.2325 (2.36)</td>
<td>.0779 (.75)</td>
<td>.0426 (.43)</td>
</tr>
<tr>
<td>29</td>
<td>Sales/ total assets</td>
<td>-.0087 (-.07)</td>
<td>-.9521 (-9.84)</td>
<td>.4133 (3.92)</td>
<td>.3849 (4.06)</td>
</tr>
<tr>
<td>30</td>
<td>▲ in sales/t assets</td>
<td>.0528 (.50)</td>
<td>.1544 (1.59)</td>
<td>-.0778 (-.75)</td>
<td>.0782 (.83)</td>
</tr>
<tr>
<td>#</td>
<td>Acting Ratio</td>
<td>Recession-Associated</td>
<td>Expansion-Associated</td>
<td></td>
<td></td>
</tr>
<tr>
<td>----</td>
<td>------------------------</td>
<td>----------------------</td>
<td>----------------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\beta_1$ (t)</td>
<td>$\beta_1$ (t)</td>
<td>$\beta_1$ (t)</td>
<td>$\beta_1$ (t)</td>
</tr>
<tr>
<td>36</td>
<td>▲ in op pr to sales</td>
<td>.2589 (2.44)</td>
<td>.2813 (2.84)</td>
<td>.0793 (.79)</td>
<td>-.0233 (-.24)</td>
</tr>
<tr>
<td>38</td>
<td>▲ in ptax inc to sale</td>
<td>.3895 (3.80)</td>
<td>.2711 (2.82)</td>
<td>.1454 (1.49)</td>
<td>.0493 (.53)</td>
</tr>
<tr>
<td>41</td>
<td>Sales to tot cash</td>
<td>-.1600 (-1.32)</td>
<td>-.5559 (-5.30)</td>
<td>-.1772 (-1.64)</td>
<td>.2994 (3.00)</td>
</tr>
<tr>
<td>47</td>
<td>Sales/ fixed assets</td>
<td>.0050 (.04)</td>
<td>-.9532 (-10.21)</td>
<td>.4090 (4.12)</td>
<td>.2927 (3.16)</td>
</tr>
<tr>
<td>48</td>
<td>▲ in prod</td>
<td>-.0373 (-.34)</td>
<td>.2878 (2.91)</td>
<td>.0368 (.35)</td>
<td>-.0941 (-.99)</td>
</tr>
<tr>
<td>58</td>
<td>▲ in op inc/ t assets</td>
<td>-.2748 (-1.90)</td>
<td>-.4401 (-3.55)</td>
<td>-.2265 (-1.89)</td>
<td>-.2115 (-1.72)</td>
</tr>
<tr>
<td>65</td>
<td>▲ in LT debt</td>
<td>-.2953 (-2.67)</td>
<td>-.2904 (-2.90)</td>
<td>.0039 (.03)</td>
<td>-.2707 (-2.79)</td>
</tr>
</tbody>
</table>
6.2.3.6 Rank Transformation Results Using Unpooled BVCP Data:

The Expansion-associated Results

Of the seven rank-transformed accounting ratios that are uniquely associated with expansion-associated BVCP SARs in the pooled tests, only one can be shown to be consistently associated across all similar unpooled BVCPs. This variable is sales to total assets. As noted earlier, this variable was significant using standardization, logs, and square root transformations. It is consistently associated across all expansion-associated BVCPs and varies across BVCP type. As found in the untransformed tests, fewer expansion-associated results are consistently significant when rank-transformations of accounting-based ratios are used.
TABLE 8
Simple Regression Results
Significant Expansion-Associated Accounting Ratios
Uniquely Associated Rank-Transformed Variables
(Unpooled BVCP Data)

<table>
<thead>
<tr>
<th>#</th>
<th>Recession-Associated</th>
<th>Expansion-Associated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>β1 (t)</td>
</tr>
<tr>
<td>1</td>
<td>Current ratio</td>
<td>.2324 (2.28)</td>
</tr>
<tr>
<td>22</td>
<td>△ in debt to equity</td>
<td>-.0306 (-.24)</td>
</tr>
<tr>
<td>24</td>
<td>△ in LT debt to equity</td>
<td>-.1381 (-1.28)</td>
</tr>
<tr>
<td>25</td>
<td>Equity/ fixed assets</td>
<td>.2663 (2.60)</td>
</tr>
<tr>
<td>29</td>
<td>Sales/ total assets</td>
<td>.4133 (3.92)</td>
</tr>
<tr>
<td>34</td>
<td>△ in gross margin</td>
<td>-.0026 (-.02)</td>
</tr>
<tr>
<td>55</td>
<td>Working cap/ t assets</td>
<td>.4260 (3.72)</td>
</tr>
</tbody>
</table>

RESULTS
6.2.4 Summary of Transformation Results

In summary, none of the popular transformation procedures that have appeared in other research, when tested in simple regression procedures, appear to improve upon the untransformed results. This result is consistent with the findings of previous research.

The transformations that form relative values appeared to improve the untransformed results. Standardization succeeded in a few cases in increasing strength of association. Rank transformations were most successful, both in discovering new ratio associations with subsequent BVCP SARS and in improving the explanatory power of several other ratio associations. Table 9, Panels A and B, present all variables that have been shown at the univariate stage to consistently vary across BVCP type in their associations with subsequent BVCP SARS. Shaded areas represent the strongest results, as measured by $r^2$. Table 9, Panel A, compares the $r^2$ for the sixteen accounting ratio associations that were found to be robustly associated to recession-associated BVCP SCARs. The standardized, rank-transformed and absolute (untransformed) results are listed. Only two variables exhibit their largest $r^2$ exclusively in the untransformed state. Six of the ratios have the largest $r^2$ when rank-transformed. Four are strongest when standardized.
Four additional variables have equally large $r^2$ using standardized or untransformed variables. These results suggest that accounting ratios may be best used in relative approaches that provide comparison valuations and rankings under similar conditions, events and states.

In Table 9, Panel B, similar results are obtained for the five accounting ratios that are robustly associated with expansion-associated BVCP SARS. In this case, no untransformed variables had the largest $r^2$ in comparison with standardized and rank-transformed variables. Four variables demonstrated the strongest results under rank transformation while one had the largest $r^2$ when standardized. A last variable had the strongest $r^2$ using either rank or standardized transformation.
Table 9A
Comparison of Association Strengths
Untransformed, Standardized and Rank Transformations
of Consistently Significant Accounting Ratios
During Recession-Associated BVCPs

<table>
<thead>
<tr>
<th>#</th>
<th>Accounting ratio variable</th>
<th>Stand</th>
<th>Rank</th>
<th>Abs</th>
<th>+-</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>Quick ratio</td>
<td>.020</td>
<td>.014</td>
<td>.023</td>
<td>+</td>
</tr>
<tr>
<td>11</td>
<td>▲ in inv</td>
<td>.012</td>
<td>.037</td>
<td>.005</td>
<td>-</td>
</tr>
<tr>
<td>12</td>
<td>▲ in sales</td>
<td>.013</td>
<td>.006</td>
<td>.013</td>
<td>-</td>
</tr>
<tr>
<td>13</td>
<td>▲ in dep</td>
<td>.016</td>
<td>.015</td>
<td>.011</td>
<td>-</td>
</tr>
<tr>
<td>15</td>
<td>Dep/plant assets</td>
<td>NSF</td>
<td>.005</td>
<td>NSF</td>
<td>-</td>
</tr>
<tr>
<td>28</td>
<td>▲ in times int earned</td>
<td>NSF</td>
<td>.007</td>
<td>NSF</td>
<td>+</td>
</tr>
<tr>
<td>35</td>
<td>Oper profit/ sales</td>
<td>.016</td>
<td>.013</td>
<td>.016</td>
<td>+</td>
</tr>
<tr>
<td>36</td>
<td>▲ in oper profit/ sales</td>
<td>NSF</td>
<td>.009</td>
<td>NSF</td>
<td>+</td>
</tr>
<tr>
<td>37</td>
<td>Pre-tax income/ sales</td>
<td>.026</td>
<td>.016</td>
<td>.026</td>
<td>+</td>
</tr>
<tr>
<td>38</td>
<td>▲ in pre-tx inc/ sales</td>
<td>NSF</td>
<td>.012</td>
<td>NSF</td>
<td>+</td>
</tr>
<tr>
<td>39</td>
<td>Net profit margin</td>
<td>.031</td>
<td>.020</td>
<td>.031</td>
<td>+</td>
</tr>
<tr>
<td>67</td>
<td>▲ in working capital</td>
<td>.011</td>
<td>NSF</td>
<td>.013</td>
<td>-</td>
</tr>
<tr>
<td>70</td>
<td>Total assets/mk equity</td>
<td>.012</td>
<td>.005</td>
<td>.011</td>
<td>-</td>
</tr>
<tr>
<td>78</td>
<td>▲ in ret earn/t assets</td>
<td>.018</td>
<td>.011</td>
<td>.017</td>
<td>+</td>
</tr>
<tr>
<td>79</td>
<td>▲ in div/ total assets</td>
<td>.015</td>
<td>.007</td>
<td>.009</td>
<td>+</td>
</tr>
<tr>
<td>81</td>
<td>Cash/ total assets</td>
<td>.007</td>
<td>.020</td>
<td>.007</td>
<td>+</td>
</tr>
</tbody>
</table>
**Table 9B**
Comparison of Association Strengths
Untransformed, Standardized and Rank Transformations
of Consistently Significant Accounting Ratios
During Expansion-Associated BVCPs

<table>
<thead>
<tr>
<th>#</th>
<th>Accounting Ratio Variable</th>
<th>Stand.</th>
<th>Ranks</th>
<th>Abs.</th>
<th>+-</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>Dep/plant assets</td>
<td>.011</td>
<td>.032</td>
<td>.010</td>
<td>+</td>
</tr>
<tr>
<td>29</td>
<td>Sales/ total assets</td>
<td>.005</td>
<td>.017</td>
<td>.005</td>
<td>+</td>
</tr>
<tr>
<td>35</td>
<td>Oper profit/ sales</td>
<td>.017</td>
<td>.015</td>
<td>.016</td>
<td>-</td>
</tr>
<tr>
<td>37</td>
<td>Pre-tax income/ sales</td>
<td>.005</td>
<td>.012</td>
<td>.006</td>
<td>-</td>
</tr>
<tr>
<td>56</td>
<td>▲ in wk cap/t assets*</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>+</td>
</tr>
<tr>
<td>39</td>
<td>Net profit margin</td>
<td>.004</td>
<td>.018</td>
<td>.005</td>
<td>-</td>
</tr>
<tr>
<td>70</td>
<td>▲ in t assets/ mk eq</td>
<td>.007</td>
<td>.007</td>
<td>.006</td>
<td>+</td>
</tr>
</tbody>
</table>

*Change in working capital to total assets was significant using only the squared transformation.
6.2.5 Summary of Simple Regression Results

Following the methodology of Beaver (1966) and Ou and Penman (1989), this stage of the empirical study has tested eighty two accounting ratios using simple linear regression in order to discover the nature of any associations with subsequent BVCP SARS. The simple regression analysis has presented evidence that the association to subsequent BVCP SARS of a substantial number of accounting ratios is a function of BVCP type. Results are strongest for recession-associated BVCP associations.

One of the objectives of the simple regression analysis was to select accounting ratio sets for subsequent testing in the multiple regression stage. The variables presented in Table 9, panels A and B, are selected because they exhibit significant associations with BVCP SARS that vary consistently across BVCP type. The next section concludes with a brief discussion of the limitations of simple regression analysis.

6.2.6 Limitations of the Simple Regression Analysis

The large number of possible accounting ratios requires data reduction techniques that can reduce the accounting data set to manageable proportions. Some researchers have used factor analytic methods to accomplish this, as noted earlier.
These methods suffer, however, from the severe non-normality of most accounting ratio distributions. Most factor-analytic methods require a multivariate normal environment. Another approach, as used in Ou and Penman (1989), involves the analysis of significant associations at the univariate level and using these as criteria for inclusion in a later multivariate stage. This methodology has the advantage of being able to isolate meaningful associations without dependence of normality assumptions in the independent variable set. It suffers, however, from a number of limitations which are discussed next.

First, a large number of possible models are precluded from examination. Multiple dependency associations may cause a given variable to be insignificant in simple regression tests but useful in multiple regression. This is particularly a problem in considering higher order transformations that may interact with lower order terms to describe a function. In this study they have been compared univariately without considering multivariate benefits that each may provide. The transformed variables may perform differently in sequential higher order multiple regression models. A multiple regression analysis of competing models would be needed to determine this and could be a reasonable extension of this study.

Second, the methodology analyzes ratios univariately in tests of hypothesis (1), thus assuming that they are used in RESULTS
a similar singular context. If this assumption does not hold, the usefulness of simple regression results are in question. Further, the regressions suffer, by design, from the errors-in-variables problem as well as inflated variances when conducting tests of significance. Coefficients can be larger in magnitude than would be the case in multiple regression. Further, the variation that could be explained by the addition of other variables, in addition to correcting for this inflation of coefficient values, would also reduce residual error, thus making tests of significance less conservative and increasing statistical power. This latter problem, while potentially worrisome, is mitigated by the fact that most of the extant AMEX/NYSE firm population is included in the sample. Thus, problems from non-random selection and design weaknesses that affect the reasonableness of any inferences are not as severe as they would be for studies with low sample size. In a sense, because the study incorporates almost the entire population of firms, it can be viewed as descriptive and therefore less sensitive to violations of the requirements that permit inferential interpretations.

Taken together, these limitations suggest the need for conformational testing, at the multiple regression level, of the results that have been found using simple regression. These results, if they support the simple regression findings and are sufficiently unhampered by interpretability weaknesses
such as collinearity among variables, would add further support for the rejection of hypothesis (1). Accordingly, these tests are conducted for part of recession-sensitive and expansion-sensitive variable sets of Table 9 as part of the multiple regression analysis.

6.3 RESULTS OF THE MULTIPLE REGRESSION ANALYSIS

The multiple regression analysis, as detailed in the previous chapter, proceeded with two specific objectives. The first objective was to confirm the results of the simple regression analysis for those variables that entered a "best" regression model, using the STEPWISE sequential selection procedure. Initial candidate variables considered for inclusion in these models (one for each BVCP type) were consistently, significantly associated in the simple regression analysis to subsequent recession-associated and expansion-associated BVCP SARS.

A limitation of this approach is that it precluded confirmational testing of hypothesis (1) for variables that, in the simple regression tests, were not consistently, significantly associated with subsequent BVCP SARS of a given BVCP type. Those variables omitted under the procedural criteria of STEPWISE were also not tested. The multiple regression testing of hypothesis (1) was therefore not as comprehensive in scope as the simple regression tests were. On
the other hand, the approach permits a retesting of the significant simple regression findings for the reduced variable set, while controlling for overfitting and underfitting in any estimation models. In the sense that the simple regression analysis can be interpreted as exploratory, these variables demonstrated the most potential to shift in their associations with subsequent BVCP SARS across BVCP type. The multiple regression analysis therefore begins by further investigating and confirming these association shifts, in accordance with hypothesis (1). The results of this portion of the analysis are contained in Section 6.3.1.

The second objective of the multiple regression analysis was to test hypotheses (2a) and (2b). These hypotheses call for the building of a prediction model using previous association data that is pooled by a given BVCP type. Again, variables with the most BVCP type sensitivity are tested for use in a "best" prediction model. The resulting model is then estimated and tested for predictive accuracy in holdout BVCP periods that vary in type, as stated in the two hypotheses. Details of the methodology are given in the previous chapter, section 5.8.2. Results of the analysis are presented in section 6.3.2.
6.3.1 Multiple Regression Test Results of Hypothesis (1)

6.3.1.1 Results of the Stepwise Sequential Selection Procedures

The analysis began by selecting for inclusion in the multiple regression analysis, from Table 9, the transformation for each ratio that yielded the largest $r^2$. In the case where a given transformation yielded an adjusted $r^2$ equal to the untransformed ratio, the untransformed variable was used in the multiple regression to facilitate interpretation. Using these variables, for recession-associated BVCP data, the stepwise sequential selection procedures produced a seven-variable model from the list of sixteen possible variables available in Table 9, Panel A. The variables were as follows: (11) change in inventory, (13) change in depreciation, (15) depreciation over plant assets, (35) operating profit over sales, (38) change in pre-tax income to sales, (67) change in working capital, and (79) change in dividends to total assets. The resulting reduced model had a C(p) statistic of 3.471 and a mean square error of .7171. The mean square error of the full model was .7211. Adjusted $R^2$ for the "best" and full models were .093 and .089 respectively. As a result of reduced data requirements, sample size increased from 829 in the case of the full model to 1047 for the "best" model.
For the expansion-associated pooled BVCP data, using the seven possible candidate variables listed in table 9, Panel B, the STEPWISE routine produced a reduced four-variable model. The variables were as follows: (15) depreciation over plant assets, (35) operating profit over sales, (56) the square of changes in working capital over total assets, and (70) change in total assets over market equity. The resulting reduced model had a C(p) statistic of 2.899 and a mean square error of .8642. The mean square error of the full model was .8699. Adjusted R² for the "best" and full models were .029 and .031 respectively. As a result of reduced data requirements, sample size increased from 1679 in the case of the full model to 1813 for the "best" model.

6.3.1.1 Multi-Collinearity Tests

As described in section 5.8.1.1, to check the variables in each "best" model for evidence of collinearity, correlation matrices were produced and examined for high correlations. Table 10, Panels A and B, present the results for the variables included in each of the "best" STEPWISE regression models derived from the variable candidates listed in Table 9, Panels A and B, respectively. No high correlations are found in either correlation matrix.
Multiple dependency tests, in addition to checking for bi-variate dependencies, also explore the possibility that dependencies involve more than two variables. Partial eigenvalue decomposition statistics for the same models are presented in Table 11, Panels A and B. No eigenvalues were near zero and no condition numbers were near the 1,000 benchmark suggested by Myers (1990). These results, together with the findings from the correlation matrices, suggest that multicollinearity is not severe for either of the models under consideration. As a result, coefficient values and signs may be interpreted with confidence as to their stability.
<table>
<thead>
<tr>
<th></th>
<th>11</th>
<th>13</th>
<th>15</th>
<th>35</th>
<th>38</th>
<th>67</th>
<th>79</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>1.00</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
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<td>.25</td>
<td>.00</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>.21</td>
<td></td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>-.02</td>
<td>.02</td>
<td>1.00</td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
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<td></td>
<td>.18</td>
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<td>-.24</td>
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<td>38</td>
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<td>.10</td>
<td>.00</td>
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<td>.02</td>
<td>.08</td>
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<td>.01</td>
<td>.08</td>
<td>1.00</td>
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</tr>
<tr>
<td>79</td>
<td>-.10</td>
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<td>.05</td>
<td>.22</td>
<td>.00</td>
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<td>1.00</td>
</tr>
<tr>
<td></td>
<td>-.04</td>
<td>-.04</td>
<td>.04</td>
<td>.16</td>
<td>.04</td>
<td>-.06</td>
<td>1.00</td>
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</tbody>
</table>

Variables are from Table 9, Panel A.
Correlations using recession-associated pooled BVCP data are listed first in each cell.
Correlations using expansion-associated pooled BVCP data are listed second in each cell.
Table 10
Panel B
Correlation Matrix
Variables in the Stepwise Model Developed From
Consistently Associated Accounting Ratios
Expansion-Associated BVCPs

<table>
<thead>
<tr>
<th></th>
<th>15</th>
<th>35</th>
<th>56</th>
<th>70</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>1.00</td>
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<td></td>
<td></td>
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<tr>
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<td></td>
</tr>
<tr>
<td>35</td>
<td>-0.24</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.29</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>56</td>
<td>0.01</td>
<td>-0.06</td>
<td>1.00</td>
<td></td>
</tr>
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<td></td>
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<td>70</td>
<td>0.09</td>
<td>-0.14</td>
<td>0.02</td>
<td>1.00</td>
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<td></td>
<td>-0.08</td>
<td>0.00</td>
<td>0.02</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Variables are from table 9, Panel B.
Correlations using expansion-associated pooled BVCP data are listed first in each cell.
Correlations using recession-associated pooled BVCP data are listed second in each cell.
Table 11
Panel A
Collinearity Diagnostics
The Stepwise Model Developed From Consistently Associated Accounting Ratios in Recession-Associated BVCPs

<table>
<thead>
<tr>
<th>#</th>
<th>Recession-Associated</th>
<th>Expansion-Associated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Eigenvalue</td>
<td>Cond.#</td>
</tr>
<tr>
<td>7</td>
<td>.4310</td>
<td>4.20</td>
</tr>
<tr>
<td>6</td>
<td>.5533</td>
<td>3.72</td>
</tr>
<tr>
<td>5</td>
<td>.7777</td>
<td>2.34</td>
</tr>
<tr>
<td>4</td>
<td>.9404</td>
<td>1.93</td>
</tr>
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</table>

Panel B
Collinearity Diagnostics
The Stepwise Model Developed From Consistently Associated Accounting Ratios in Expansion-Associated BVCPs

<table>
<thead>
<tr>
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<th>Expansion-Associated</th>
<th>Recession-Associated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<td>Cond.#</td>
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<tr>
<td>4</td>
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<td>3</td>
<td>.9487</td>
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<td>2</td>
<td>1.0446</td>
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<tr>
<td>1</td>
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</tbody>
</table>
6.3.1.2 Results of The Stepwise "Best" Models

Table 12, Panel A, presents the results of the STEPWISE "best" model derived from the variable set for recession-associated BVCPs (listed in Table 9, Panel A). Generally, the test results of the multivariate model confirm what was found in the univariate tests. In particular, the overall variable set is far more sensitive to recession-associated subsequent BVCP SARs. Adjusted \( r^2 \) using recession-associated pooled BVCP data is .095. When the same regression is repeated using expansion-associated BVCP data, Adjusted \( r^2 \) falls to only .011.

All of the ratios except change in working capital (#67) are significant at the .05 level when recession-associated pooled BVCP data are used. The signs of all coefficients are consistent with the univariate findings. On the other hand, in a similar regression model, using expansion-associated BVCP data, only the coefficients for change in depreciation (#13) and dividends over total assets (#79) are significant. In both of these cases, the coefficient sign reverses across BVCP type. These results suggest that these accounting ratios' association with subsequent BVCP SARs varies across BVCP type.
The results for the STEPWISE "best" model derived from the expansion-sensitive variable set (listed in Table 9, Panel B), are presented in Table 12, Panel B. All of the four variables in the best model are significantly associated with subsequent pooled expansion-associated BVCP SARS. Further, the signs of the association, when expansion-associated pooled BVCP data are used, confirm the univariate findings. When recession-associated BVCP data are used for the same variables, the signs reverse or become insignificant. Strength of association for the model is approximately unchanged across BVCP type.

In summary, the results of both sets of multiple regressions confirm the univariate findings when pooled BVCP data are used. This provides further evidence that hypothesis (1) can be rejected for these variables.
Table 12  
Panel A  
Multiple Regression Results  
The Stepwise Model Developed From  
Consistently Associated Accounting Ratios  
in Recession-Associated BVCPs  
*Pooled BVCP Data*  

<table>
<thead>
<tr>
<th></th>
<th>Acct Var.</th>
<th>Rec-Associated</th>
<th>Exp-Associated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$\beta$</td>
<td>$t$</td>
</tr>
<tr>
<td>11</td>
<td>▲ in inv</td>
<td>-.5573</td>
<td>-4.75$^*$</td>
</tr>
<tr>
<td>13</td>
<td>▲ in dep</td>
<td>-.0861</td>
<td>-2.33$^*$</td>
</tr>
<tr>
<td>15</td>
<td>Dep/pl assets</td>
<td>-.2194</td>
<td>-1.97$^*$</td>
</tr>
<tr>
<td>35</td>
<td>Op pr/ sales</td>
<td>.2560</td>
<td>4.63$^*$</td>
</tr>
<tr>
<td>38</td>
<td>▲ p-tx inc/s</td>
<td>.4047</td>
<td>3.86$^*$</td>
</tr>
<tr>
<td>67</td>
<td>▲ in work cap</td>
<td>.0310</td>
<td>.26</td>
</tr>
<tr>
<td>79</td>
<td>div/ta</td>
<td>.1009</td>
<td>2.41$^*$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Adjusted $r^2$</th>
<th>.095</th>
<th>.011</th>
</tr>
</thead>
<tbody>
<tr>
<td>F</td>
<td></td>
<td>16.81$^*$</td>
<td>2.81$^*$</td>
</tr>
<tr>
<td>N</td>
<td></td>
<td>1047</td>
<td>1132</td>
</tr>
</tbody>
</table>

* indicates the coefficient is significantly different from 0 at the .05 level.
Table 12
Panel B
Multiple Regression Results
The Stepwise Model Developed From
Consistently Associated Accounting Ratios
in Expansion-Associated BVCPs
*Pooled BVCP Data*

<table>
<thead>
<tr>
<th>#</th>
<th>Acct Var.</th>
<th>Exp-Associated</th>
<th></th>
<th>Rec-Associated</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>Dep/pl assets</td>
<td>.3369</td>
<td>4.23*</td>
<td>-.1498</td>
<td>-1.72*</td>
</tr>
<tr>
<td>35</td>
<td>Op pr/sales</td>
<td>-.1014</td>
<td>-2.55*</td>
<td>.1387</td>
<td>4.75*</td>
</tr>
<tr>
<td>56</td>
<td>▲ in wc / ta</td>
<td>.0041</td>
<td>2.62*</td>
<td>-.0255</td>
<td>-.87</td>
</tr>
<tr>
<td>70</td>
<td>▲ in ta/me</td>
<td>.0759</td>
<td>2.88*</td>
<td>-.1182</td>
<td>-5.02*</td>
</tr>
<tr>
<td></td>
<td>Adjusted r²</td>
<td>.029</td>
<td></td>
<td>.032</td>
<td></td>
</tr>
<tr>
<td></td>
<td>F</td>
<td>14.69*</td>
<td></td>
<td>15.40*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>1813</td>
<td></td>
<td>1736</td>
<td></td>
</tr>
</tbody>
</table>

* indicates the coefficient is significantly different from 0 at the .05 level.
^ indicates the coefficient is significantly different from 0 at the .10 level.
6.3.1.3 Other Possible Explanations— Confounding Events

The results described above may be explained by several other phenomenon unrelated to BVCP type. One possibility, as with the univariate results, is that the results are sample-specific. Other confounding events, such as the occurrence of inflation, world trading patterns, etc., may have caused the results. To provide evidence that the results are not sample-specific, unpooled BVCP data were used in four separate regressions. Two multiple regressions were conducted for each BVCP type, in a procedure similar to the earlier simple regression analyses. The results for each of the two "best" stepwise models are presented in Table 13, Panels A and B.

The sub-period regressions generally confirm the pooled multivariate findings. All of the significant coefficients in the regressions for both models, using pooled BVCP data, generally have the same sign in the regressions that used unpooled data. One important exception in Panel A concerns operating profit over sales (#35), which is now significant and positive in one expansion-associated BVCP as well as both recession-associated BVCPs. This result suggests that the negative coefficient sign detected for this variable, using pooled expansion-associated BVCP data, may be an artifact that is not specific to expansion-associated BVCPs. Hypothesis (1) cannot therefore be rejected conclusively for this variable.
In most cases, variables significant in the pooled regressions remained so in the unpooled tests. Exceptions in Panel A (the regressions using the recession-sensitive STEPWISE "best" model developed from the variables in Table 9, Panel A) are change in depreciation (#13), change in pre-tax income to sales (#38) and change in dividends to total assets (#79). These variables all exhibit consistent coefficient signs and magnitude but are significant in only one BVCP sub-period. Depreciation over plant assets (#15) was newly significant in a recession-associated BVCP, but the sign reversed across BVCP type. Note also that the entire regression, using expansion-associated BVCP data from the period 1974-1980, is insignificant at the .05 level.\(^6^8\)

In the regressions presented in Table 13, panel B, which used the STEPWISE "best" model developed from the expansion-sensitive variables in Table 9, panel B, the coefficients of each variable shift in sign consistently across BVCP type. Again, however, not all variable coefficients are significant in both BVCP sub-periods. The signs exhibited by the variable coefficients are congruent with the earlier univariate results.

\(^6^8\)The coefficient for change in inventory (#11) is significant and negative in this regression, as it was in both recession-associated BVCPs. If the regression was significantly associated to subsequent expansion-associated SARs, further coefficient analysis would suggest that hypothesis (1) cannot be rejected for this variable. The regression, however, was not significant.
In summary, the sub-period regressions suggest that the findings are not the product of sample-specific confounding events. Certain accounting ratio associations generally appear to vary consistently across BVCP type in multivariate and univariate settings. Further, the strength of association appears to vary across BVCP type when the recession-sensitive STEPWISE model (Tables 12 and 13, Panel A) is used. The associations to subsequent BVCP S ARs are much stronger using recession-associated BVCP data.
### Table 13

#### Panel A

**Multiple Regression Results**

The Stepwise Model Developed From Consistently Associated Accounting Ratios in Recession-Associated BVCPs

*Unpooled BVCP Regression Results*

<table>
<thead>
<tr>
<th>#</th>
<th>Variable</th>
<th>Recession BVCPs</th>
<th>Expansion BVCPs</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>▲ in inv</td>
<td>-.3227*</td>
<td>-.6047*</td>
</tr>
<tr>
<td>13</td>
<td>▲ in dep</td>
<td>-.0006</td>
<td>-.3040*</td>
</tr>
<tr>
<td>15</td>
<td>Dep/pl assets</td>
<td>-.4250*</td>
<td>-.1229*</td>
</tr>
<tr>
<td>35</td>
<td>Op pr/ sales</td>
<td>.1697*</td>
<td>.4014*</td>
</tr>
<tr>
<td>38</td>
<td>▲ p-tx inc/s</td>
<td>.4475*</td>
<td>.2292</td>
</tr>
<tr>
<td>67</td>
<td>▲ in work cap</td>
<td>-.0550</td>
<td>-.1828</td>
</tr>
<tr>
<td>79</td>
<td>div/ta</td>
<td>.1070*</td>
<td>.1059</td>
</tr>
<tr>
<td></td>
<td>Adjusted ( r^2 )</td>
<td>.078</td>
<td>.141</td>
</tr>
<tr>
<td></td>
<td>( F )</td>
<td>6.91*</td>
<td>14.11*</td>
</tr>
<tr>
<td></td>
<td>( N )</td>
<td>490</td>
<td>559</td>
</tr>
</tbody>
</table>

Coefficients with * subscript significant at the .05 level.
Coefficients with ^ subscript significant at the .10 level.
### Table 13

**Panel B**

**Multiple Regression Results**
The Stepwise Model Developed From
Consistently Associated Accounting Ratios
in Expansion-Associated BVCPs

*Unpooled BVCP Regression Results*

<table>
<thead>
<tr>
<th>#</th>
<th>Variable</th>
<th>Expansion BVCPs</th>
<th>Recession BVCPs</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>dep/p assets</td>
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<td>.1112</td>
</tr>
<tr>
<td>35</td>
<td>op pr/sales</td>
<td>-.0054</td>
<td>-.1096*</td>
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<tr>
<td>56</td>
<td>▲ in wc/ta</td>
<td>.0045*</td>
<td>.2980*</td>
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<tr>
<td>70</td>
<td>▲ in ta/m eq</td>
<td>.0185</td>
<td>.1469*</td>
</tr>
<tr>
<td></td>
<td>Adjusted r²</td>
<td>.046</td>
<td>.030</td>
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<tr>
<td></td>
<td>F</td>
<td>11.15*</td>
<td>8.83*</td>
</tr>
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<td></td>
<td>N</td>
<td>829</td>
<td>984</td>
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</tbody>
</table>

Coefficients with * subscript significant at the .05 level. Coefficients with ^ subscript significant at the .10 level.
6.3.1.4 Other Possible Explanations—Model Misspecifications

Another possible explanation for the findings may be that the regression model is cross-sectionally misspecified. To check for this possibility, tests were conducted on each of the two models to determine if high influence observations (outliers with leverage) differed from the rest of the sample, on average, in certain cross-sectional firm characteristics such as size, growth and sales.

The results for the STEPWISE model derived from the recession-sensitive variables of Table 9, Panel A are reported in Table 14, Panel A. In tests for differences across the two groups (high influence and non-influence), asset size, as measured by total assets, was insignificant at the .05 level for recession-associated and expansion-associated BVCPs. On the other hand, growth (proxied by change in retained earnings and deflated by total equity) was significantly different in both BVCP types. Sales were significantly different only when regressions used pooled expansion-associated BVCP data. The indicated cutoffs are .15 and above for growth and firms with sales less than 30 million. Using these cutoffs, more than 40% of all high influence points, as defined by the DFFITS measure, would be deleted.
The results for the STEPWISE model derived from the expansion-sensitive variables of Table 9, Panel B are presented in Table 14, Panel B. The results mimic those of the recession-sensitive model. Degree of association, means for each group, and percentile cutoffs vary however.

To simplify the interpretation across models, the data were screened for sales and growth criteria and all observations were deleted with sales volume less than 30 million and growth rates greater than 15% per year. These cutoffs represent the most conservative values of all the model and sample tests conducted. Further, at least 40% of all high-influence data were thereby deleted from all samples. The remaining data were then re-tested and the coefficients checked for evidence of any change when compared to the results of the full sample.

The results for the "best" recession-sensitive model (derived using STEPWISE selection from the candidate variables of Table 9, Panel A) are presented in Table 15, Panel A. The screening criteria resulted in deletions of 237 observations when recession-associated BVCP data were used. This left 810 observations for use in the new regression. Similarly, for the regression using expansion-associated BVCP data, 225 observations were deleted, leaving 907 in the remaining data set. The regression results again confirm the earlier findings. In every case where variable coefficients are

RESULTS
significant, the signs of those coefficients reverse or are insignificant across BVCP type. Further, the signs for each coefficient are congruous with the earlier findings. The strength of overall association, as measured by adjusted $R^2$, is again much higher when recession-associated BVCP data are used.

The results for the "best" expansion sensitive model (derived using STEPWISE selection from the candidate variables of Table 9, Panel B) are presented in Table 15, Panel B. A total of 491 observations were deleted from the regression using expansion-associated BVCP data, leaving a reduced data set of 1322 firm-observations. In the regression estimated with recession-associated BVCP data, 556 observations were deleted, leaving 1180 in the remaining dataset. The results in panel B again show a consistent pattern of reversal of sign across BVCP type. In every case where a coefficient sign is significant, the sign significantly reverses (or reverses and is insignificant) across BVCP type. The results, taken together, suggest that the findings are robust in this sub-population of firm-observations. The findings cannot be explained by the cross-sectional model mis-specifications examined.
Table 14
Panel A
Multiple Regression Results
The Stepwise Model Developed From
Consistently Associated Accounting Ratios
in Recession-Associated BVCPs
*Average Size, Sales and Growth*
*High-Influence and Low-Influence Observations*

<table>
<thead>
<tr>
<th></th>
<th>Inf</th>
<th>Non-Inf</th>
<th>F</th>
<th>p**</th>
<th>.9/.1^</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size- recession associated BVCPs</td>
<td>300</td>
<td>702</td>
<td>1.34</td>
<td>.246</td>
<td>NMF</td>
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<tr>
<td>Size- expansion associated BVCPs</td>
<td>220</td>
<td>789</td>
<td>2.59</td>
<td>.107</td>
<td>NMF</td>
</tr>
<tr>
<td>Sales-recession associated BVCPs</td>
<td>371</td>
<td>760</td>
<td>2.24</td>
<td>.135</td>
<td>NMF</td>
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<td>Sales-expansion associated BVCPs</td>
<td>203</td>
<td>891</td>
<td>6.03</td>
<td>.014</td>
<td>30</td>
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<td>Growth-Recession associated BVCPs*</td>
<td>1564</td>
<td>687</td>
<td>29.82</td>
<td>.000</td>
<td>1500</td>
</tr>
<tr>
<td>Growth-Expansion associated BVCPs*</td>
<td>1617</td>
<td>701</td>
<td>28.50</td>
<td>.000</td>
<td>1500</td>
</tr>
</tbody>
</table>

"Inf" column contains the mean value for the criterion for the influence group.
"Non-Inf" column contains the mean value for the criterion for the non-influence group.
*Growth values are stated after multiplication by the constant 10000.
**p represents the p-value.
\^refers to the applicable decile cutoff value (.90 or .10 decile).
### Table 14
Panel B
Multiple Regression Results
The Stepwise Model Developed From
Consistently Associated Accounting Ratios
in Expansion-Associated BVCPs
*Average Size, Sales and Growth*
*High-Influence and Low-Influence Observations*

<table>
<thead>
<tr>
<th></th>
<th>Inf</th>
<th>Non-Inf</th>
<th>F</th>
<th>p</th>
<th>.9/.1</th>
</tr>
</thead>
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<tr>
<td>Size- recession</td>
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<td>608</td>
<td>3.49</td>
<td>.061</td>
<td>NMF</td>
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<tr>
<td>associated BVCPs</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Size- expansion</td>
<td>220</td>
<td>789</td>
<td>3.50</td>
<td>.061</td>
<td>NMF</td>
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<td>associated BVCPs</td>
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<tr>
<td>Sales-recession</td>
<td>80</td>
<td>514</td>
<td>5.62</td>
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<td>15</td>
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</tr>
<tr>
<td>Sales-expansion</td>
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<td>605</td>
<td>5.40</td>
<td>.020</td>
<td>15</td>
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</tr>
<tr>
<td>Growth-Recession</td>
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<td>.000</td>
<td>2000</td>
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<tr>
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<tr>
<td>Growth-Expansion</td>
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<td>927</td>
<td>22.14</td>
<td>.000</td>
<td>2000</td>
</tr>
<tr>
<td>associated BVCPs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

"Inf" column contains the mean value for the criterion for the influence group.
"Non-Inf" column contains the mean value for the criterion for the non-influence group.
*Growth values are stated after multiplication by the constant 10000.*
<table>
<thead>
<tr>
<th>#</th>
<th>Acct Var.</th>
<th>Rec-Associated</th>
<th>Exp-Associated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>t</td>
<td>B</td>
</tr>
<tr>
<td>11</td>
<td>△ in inv</td>
<td>-.7118</td>
<td>-4.81*</td>
</tr>
<tr>
<td>13</td>
<td>△ in dep</td>
<td>-.2509</td>
<td>-3.26*</td>
</tr>
<tr>
<td>15</td>
<td>Dep/pl assets</td>
<td>-.2126</td>
<td>-1.71*</td>
</tr>
<tr>
<td>35</td>
<td>Op pr/ sales</td>
<td>.2384</td>
<td>3.04*</td>
</tr>
<tr>
<td>38</td>
<td>△ p-tx inc/s</td>
<td>.4028</td>
<td>3.46*</td>
</tr>
<tr>
<td>67</td>
<td>△ in work cap</td>
<td>.1935</td>
<td>1.05</td>
</tr>
<tr>
<td>79</td>
<td>div/ta</td>
<td>.1023</td>
<td>1.96*</td>
</tr>
</tbody>
</table>

Adjusted r^2
- Rec-Associated: .111
- Exp-Associated: .018

F
- Rec-Associated: 15.52
- Exp-Associated: 3.42*

N
- Rec-Associated: 810
- Exp-Associated: 907

* indicates the coefficient is significantly different from 0 at the .05 level.
^ indicates the coefficient is significantly different from 0 at the .10 level.
Table 15
Panel B
Multiple Regression Results
The Stepwise Model Developed From
Consistently Associated Accounting Ratios
in Expansion-Associated Pooled BVCPs
*Low Sales/ High Growth Firms Deleted*

<table>
<thead>
<tr>
<th>#</th>
<th>Acct Var.</th>
<th>Exp-associated</th>
<th>Rec-associated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>B</td>
<td>t</td>
</tr>
<tr>
<td>15</td>
<td>Dep/pl assets</td>
<td>.4622</td>
<td>4.85*</td>
</tr>
<tr>
<td>35</td>
<td>Op pr/ sales</td>
<td>-.1557</td>
<td>-2.67*</td>
</tr>
<tr>
<td>56</td>
<td>▲ in wc / ta</td>
<td>.1327</td>
<td>.56</td>
</tr>
<tr>
<td>70</td>
<td>▲ in ta/me</td>
<td>.0909</td>
<td>2.69*</td>
</tr>
<tr>
<td></td>
<td>Adjusted r²</td>
<td>.047</td>
<td></td>
</tr>
<tr>
<td></td>
<td>F</td>
<td>17.61*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>1322</td>
<td></td>
</tr>
</tbody>
</table>

* indicates the coefficient is significantly different from 0 at the .05 level.
^ indicates the coefficient is significantly different from 0 at the .10 level.
6.3.1.5 Outlier Effects

The findings could also be the result of outliers that have significantly influenced the regression line. To test for this possibility, outliers were deleted as specified in section 5.8.1. Each accounting ratio was ranked into twenty deciles. Any observation that contained a single accounting ratio rank in the first or twentieth decile was then deleted. As a result of this screening, 438 observations were deleted in the STEPWISE "best" model that used pooled recession-associated BVCP data and was developed from the recession-sensitive variables of Table 9, Panel A. This left 609 observations that contained no ratio outliers. Using the same model and expansion-associated BVCP data, 456 observations were deleted leaving 676 observations that contained no outliers. The results of these regressions are described in Table 16, Panel A.

The results for those observations with no outliers are almost identical with those of the entire sample (Table 12). When recession-associated pooled BVCP data are used, the signs of all coefficients remain the same. There are some differences in significance of association. The coefficient for depreciation over plant assets (#15) is now insignificant. Also, changes in working capital (#67) is now positive and significantly associated with subsequent pooled recession-effects.
associated BVCP SARs. One substantive change concerns the coefficient for changes in pre-tax income to sales (#38). This coefficient is positive and significant using expansion-associated BVCP data. The coefficient direction and significance no longer varies across BVCP type. The results for this coefficient suggest hypothesis (1) cannot be rejected for this variable when the effect of outliers are removed.

The results for the regressions using the STEPWISE model derived from the variables in Table 9, Panel B are presented in Table 16, Panel B. Using expansion-associated BVCP data in the model, 589 observations were deleted, leaving 1224 observations that contained no ratio outliers. When recession-associated BVCP were used, 563 observations were identified as outliers and deleted, leaving 1173 observations that contained no outliers. For these regressions, the results again mimic the results of table 12, where no outliers were deleted. This suggest that the findings are not driven by accounting ratio outlier observations. Two differences with the earlier results are: Changes in working capital over total assets (#56) which is now positively, significantly associated with subsequent BVCP SARs across both BVCP types; and change in total assets over market equity, which now has an insignificant coefficient when expansion-associated BVCP data are used.
<table>
<thead>
<tr>
<th>#</th>
<th>Acct Var.</th>
<th>Rec-Associated</th>
<th>Exp-Associated</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>▲ in inv</td>
<td>-.7546</td>
<td>-.2576</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-4.05^*</td>
<td>-1.62</td>
</tr>
<tr>
<td>13</td>
<td>▲ in dep</td>
<td>-.3208</td>
<td>.7993</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-2.23^*</td>
<td>3.64^*</td>
</tr>
<tr>
<td>15</td>
<td>Dep/pl assets</td>
<td>-.2320</td>
<td>.1481</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-1.55</td>
<td>1.05</td>
</tr>
<tr>
<td>35</td>
<td>Op pr/ sales</td>
<td>.2296</td>
<td>-.0223</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.13^*</td>
<td>-.17</td>
</tr>
<tr>
<td>38</td>
<td>▲ p-tx inc/s</td>
<td>.3119</td>
<td>.3367</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.13^*</td>
<td>2.33^*</td>
</tr>
<tr>
<td>67</td>
<td>▲ in work cap</td>
<td>.6424</td>
<td>.3581</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.19^*</td>
<td>1.40</td>
</tr>
<tr>
<td>79</td>
<td>div/ta</td>
<td>.2530</td>
<td>-.0764</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.84^*</td>
<td>-.97</td>
</tr>
<tr>
<td></td>
<td>Adjusted r²</td>
<td>.083</td>
<td>.029</td>
</tr>
<tr>
<td></td>
<td>F</td>
<td>8.87</td>
<td>3.94</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>609</td>
<td>676</td>
</tr>
</tbody>
</table>

* indicates the coefficient is significantly different from 0 at the .05 level.
^ indicates the coefficient is significantly different from 0 at the .10 level.
Table 16
Panel B
Multiple Regression Results
The Stepwise Model Developed From Consistently Associated Accounting Ratios in Expansion-Associated BVCPs
*Observations with Accounting Ratio Outliers Deleted*

<table>
<thead>
<tr>
<th>#</th>
<th>Acct Var.</th>
<th>Exp-Associated</th>
<th>Rec-Associated</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>Dep/pl assets</td>
<td>.3314</td>
<td>-.2003</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3.18&quot;</td>
<td>-1.76&quot;</td>
</tr>
<tr>
<td>35</td>
<td>Op pr/ sales</td>
<td>-.2032</td>
<td>.1983</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-2.87&quot;</td>
<td>3.77&quot;</td>
</tr>
<tr>
<td>56</td>
<td>△ in wc / ta</td>
<td>1.8158</td>
<td>2.5890</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.05&quot;</td>
<td>2.62&quot;</td>
</tr>
<tr>
<td>70</td>
<td>△ in ta/me</td>
<td>-.0286</td>
<td>-.1643</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-.57</td>
<td>-3.85&quot;</td>
</tr>
<tr>
<td></td>
<td>Adjusted r²</td>
<td>.019</td>
<td>.033</td>
</tr>
<tr>
<td></td>
<td>F</td>
<td>7.04&quot;</td>
<td>11.13&quot;</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>1224</td>
<td>1173</td>
</tr>
</tbody>
</table>

* indicates the coefficient is significantly different from 0 at the .05 level.
^ indicates the coefficient is significantly different from 0 at the .10 level.
6.3.1.6 Industry Effects-Tests Using Dummy Variables for First Digit of the Industry Code

The results, as discussed in chapter 5, section 5.8.1.4, may also be suspect because of industry dependencies causing correlations in the regression residuals and spurious results. Two approaches were used in an attempt to control for such industry effects. In the first approach, dummy variables are included in the regressions of each best model, based on the first digit of the four digit DNUM code. The expanded model was then tested for significance over and above the reduced model. The regressions were also analyzed for changes in coefficient signs and significance when industry variables were added to control for industry dependencies. In addition, firms with sales less than 30 million dollars or growth rates greater than .15 were also deleted. This was done because these cross-sectional characteristics were found earlier to be an additional source of model misspecification. The results are presented in Table 17, Panels A and B, for the recession-sensitive and expansion-sensitive "best" models respectively, as with all the previous analyses. The F-test for the incremental significance of the expanded model is also presented. In all cases, the dummy industry variables resulted in a significantly improved expanded model.
In Panel A, the coefficient changes are minimal and essentially support the earlier findings. Where coefficients are significant using recession-associated BVCP data to estimate the model, they become either insignificant or experience sign reversal when expansion-associated BVCP data are used. The overall association strength, as measured by adjusted $r^2$, improves in both expanded models but the wide gap in magnitude of association across BVCP type remains.

In Panel B, the results also confirm the earlier findings. Sign reversal occurs across BVCP type for every variable except operating profit to sales (♯35). The results for this variable, with respect to coefficient sign across BVCP type, are ambiguous. When expansion-associated BVCP data are used, the variable becomes insignificant at the .10 level or lower.

In summary, with the exception of operating profit to sales (♯35), controlling for industry effects with dummy variables for the first DNUM digit does not appear to substantively alter earlier findings. Hypothesis (1) can still be rejected for most of the other variables tested.
Table 17
Panel A
Multiple Regression Results
The Stepwise Model Developed From
Consistently Associated Accounting Ratios
in Recession-Associated BVCPs
*Dummy Variables added for Industry Code First Digit*

<table>
<thead>
<tr>
<th>#</th>
<th>Acct Var.</th>
<th>Rec-Associated</th>
<th>Exp-Associated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>( \beta )</td>
<td>( t )</td>
</tr>
<tr>
<td>11</td>
<td>( \Delta ) in inv</td>
<td>-.7359</td>
<td>-4.98*</td>
</tr>
<tr>
<td>13</td>
<td>( \Delta ) in dep</td>
<td>-.2468</td>
<td>-3.15*</td>
</tr>
<tr>
<td>15</td>
<td>Dep/pl assets</td>
<td>-.1440</td>
<td>-1.11</td>
</tr>
<tr>
<td>35</td>
<td>Op pr/ sales</td>
<td>.2773</td>
<td>3.23*</td>
</tr>
<tr>
<td>38</td>
<td>( \Delta ) p-tx inc/s</td>
<td>.3796</td>
<td>3.27*</td>
</tr>
<tr>
<td>67</td>
<td>( \Delta ) in work cap</td>
<td>.2000</td>
<td>1.24</td>
</tr>
<tr>
<td>79</td>
<td>div/ta</td>
<td>.0663</td>
<td>1.67*</td>
</tr>
<tr>
<td></td>
<td>Adjusted ( r^2 )</td>
<td>.131</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( F )</td>
<td>9.71*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>F-Ind var.</td>
<td>3.53*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>810</td>
<td></td>
</tr>
</tbody>
</table>

* indicates the coefficient is significantly different from 0 at the .05 level.
^ indicates the coefficient is significantly different from 0 at the .10 level.
F-Ind Var. refers to the F test used to detect significance of the expanded model that included industry dummy variables over the reduced, "accounting ratio only" model.
Table 17
Panel B
Multiple Regression Results
The Stepwise Model Developed From
Consistently Associated Accounting Ratios
in Expansion-Associated BVCPs
*Dummy Variables Added For Industry Code First Digit*

<table>
<thead>
<tr>
<th>#</th>
<th>Acct Var.</th>
<th>Exp-Associated</th>
<th>Rec-Associated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>( \beta )</td>
<td>( t )</td>
</tr>
<tr>
<td>15</td>
<td>Dep/pl assets</td>
<td>.3581</td>
<td>3.45*</td>
</tr>
<tr>
<td>35</td>
<td>Op pr/ sales</td>
<td>.0346</td>
<td>.50</td>
</tr>
<tr>
<td>56</td>
<td>( \Delta ) in wc / ta</td>
<td>.0293</td>
<td>.12</td>
</tr>
<tr>
<td>70</td>
<td>( \Delta ) in ta/me</td>
<td>.0980</td>
<td>2.80*</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Exp-Associated</th>
<th>Rec-Associated</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adjusted ( r^2 )</td>
<td>.072</td>
<td>.072</td>
</tr>
<tr>
<td>F</td>
<td>10.16*</td>
<td>9.31*</td>
</tr>
<tr>
<td>F-Ind. var.</td>
<td>5.30*</td>
<td>5.44</td>
</tr>
<tr>
<td>N</td>
<td>1287</td>
<td>1180</td>
</tr>
</tbody>
</table>

* indicates the coefficient is significantly different from 0 at the .05 level.
\(^\ast\) indicates the coefficient is significantly different from 0 at the .10 level.
F-Ind Var. refers to the F test used to detect significance of the expanded model that included industry dummy variables over the reduced, "accounting ratio only" model.
6.3.1.6 Industry Effects—Control Using Dummy variables for Entire Industry Code

Using the first, and least specific, digit of the industry code to partition firm observations into groups may not adequately control for industry dependency effects. A second, more general test and control was thus applied. This involved ranking regression residuals into quartiles and then testing for dependency between the residual quartile ranking and the full 4-digit industry code. This more general test has the advantage of using a more specific industry code and being more sensitive to non-linear dependencies. On the other hand, because at least 80% of the resulting contingency table cells must have an expected value of 5 or greater for the test to be valid, a number of industries with lesser numbers of firms (less than 16) had to be excluded, limiting the generalizability of results. The full procedures are described in section 5.8.1.4.

Table 18, Panel A, presents the results for the recession-sensitive STEPWISE "best" model derived from the variables in Table 9, Panel A. The Chi-Square industry dependency test statistic is given for regressions with and without dummy industry code variables added. The chi-square statistic with added industry code dummy variables is insignificant at the .10 level or lower. The added variables

RESULTS
thus fully capture industry dependency as proxied by the quartile residual ranks. Further, the added variables add incremental explanatory power as evidenced by the significant partial F-test.

When recession-associated BVCP data were used to estimate the model, a total of 54 industry codes and 810 observations were reduced to a sub-set of 19 industry codes and 637 observations. Similarly, for expansion-associated BVCP data, 99 observations were deleted, leaving a subset of 21 industry codes and 740 observations.

The signs of all coefficients in Table 18, Panel A, are similar to the earlier findings and confirm the simple regression results, where significant, with one exception. Change in inventory (#11) is now negative and significant at the .05 level across both BVCP types. This suggests that industry mis-specification may have contributed to the earlier shifts detected for this variable. Of course, an alternative explanation is that industry groups with large numbers of firms (i.e. non-oligopolistic) may not experience shifts in association across BVCP type for changes in inventory. In any event, the test calls into question exactly what is driving the association shift across BVCP type for this variable.

Table 18, Panel B presents the results for the expansion STEPWISE "best" model derived from the variables in Table 9, Panel B. Chi-square is insignificant for the model estimated RESULTS
with expansion-associated BVCP data when industry codes are controlled. The added industry variables fully capture industry dependency as proxied by the quartile residual ranks. On the other hand, chi-square remains significant for the model estimated with recession-associated BVCP data, even after industry codes are controlled. This suggests the presence of non-linear industry dependencies for this case and weakens interpretability of the second model.69

In both of the regressions presented in Panel B, the added variables add incremental explanatory power as evidenced by the significant partial F-test. When expansion-associated BVCP data were used to estimate the model, a total of 59 industry codes and 1287 observations were reduced to a sub-set of 25 industry codes and 1134 observations. Similarly, for recession-associated BVCP data, 205 observations were deleted, leaving a subset of 22 industry codes and 975 observations.

With the exception of operating profit to sales (#35) the signs of the coefficients are congruent with earlier results. Where the coefficients are significant, they confirm the simple regression findings that shifts in association occurred across BVCP type, even when industry dependency is fully

69An alternative explanation is measurement error with respect to the 4-digit code. Industry mis-classifications may cause linear residual errors to remain dependent.
controlled and the sample is screened for firms with low sales and high rates of growth.
Table 18
Panel A
Multiple Regression Results
The Stepwise Model Developed From Consistently Associated Accounting Ratios in Recession-Associated BVCPs
*Dummy Variables added for 4-Digit Industry Code*

<table>
<thead>
<tr>
<th>#</th>
<th>Acct Var.</th>
<th>β</th>
<th>t</th>
<th>β</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>▲ in inv</td>
<td>-.5542</td>
<td>-3.34*</td>
<td>-.3214</td>
<td>-2.18*</td>
</tr>
<tr>
<td>13</td>
<td>▲ in dep</td>
<td>-.1829</td>
<td>-1.67^</td>
<td>.3998</td>
<td>3.08*</td>
</tr>
<tr>
<td>15</td>
<td>Dep/pl assets</td>
<td>-.0071</td>
<td>.04</td>
<td>.2407</td>
<td>1.70*</td>
</tr>
<tr>
<td>35</td>
<td>Op pr/ sales</td>
<td>.1632</td>
<td>1.49</td>
<td>.0789</td>
<td>.64</td>
</tr>
<tr>
<td>38</td>
<td>▲ p-tx inc/s</td>
<td>.4699</td>
<td>3.65*</td>
<td>.0641</td>
<td>.50</td>
</tr>
<tr>
<td>67</td>
<td>▲ in work cap</td>
<td>.0029</td>
<td>.01</td>
<td>.1488</td>
<td>.75</td>
</tr>
<tr>
<td>79</td>
<td>div/ta</td>
<td>.0397</td>
<td>.71</td>
<td>-.0485</td>
<td>-.99</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Rec-Associated</th>
<th>Exp-Associated</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adjusted r²</td>
<td>.167</td>
<td>.087</td>
</tr>
<tr>
<td>F</td>
<td>6.10*</td>
<td>3.63*</td>
</tr>
<tr>
<td>Chi-Sq(No-ind)</td>
<td>100.25*</td>
<td>113.14*</td>
</tr>
<tr>
<td>Chi-Sq(Ind)</td>
<td>41.28</td>
<td>40.98</td>
</tr>
<tr>
<td>F-Ind var.</td>
<td>4.21*</td>
<td>3.45*</td>
</tr>
<tr>
<td>N</td>
<td>637</td>
<td>740</td>
</tr>
</tbody>
</table>

* indicates the coefficient is significantly different from 0 at the .05 level.
^ indicates the coefficient is significantly different from 0 at the .10 level.

F-Ind Var. refers to the F test used to detect significance of the expanded model that included industry dummy variables over the reduced, "accounting ratio only" model.
Chi-square (No-ind) is the test statistic for dependency tests of the contingency table 4xn, where n is the number of industry codes (4-digit) and 4 represents residual quartiles from regressions with no industry controls added.
Chi-square (Ind) is same as above with industry controls.
Table 18
Panel B
Multiple Regression Results
The Stepwise Model Developed From
Consistently Associated Accounting Ratios
in Expansion-Associated BVCPs
*Dummy Variables Added For 4-Digit Industry Code*

<table>
<thead>
<tr>
<th>#</th>
<th>Acct Var.</th>
<th>B</th>
<th>t</th>
<th>B</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>Dep/pl assets</td>
<td>.3994</td>
<td>3.15*</td>
<td>.0600</td>
<td>.43</td>
</tr>
<tr>
<td>35</td>
<td>Op pr/ sales</td>
<td>.0355</td>
<td>.45</td>
<td>.0238</td>
<td>.35</td>
</tr>
<tr>
<td>56</td>
<td>▲ in wc / ta</td>
<td>.4054</td>
<td>1.57</td>
<td>-.1881</td>
<td>-.59</td>
</tr>
<tr>
<td>70</td>
<td>▲ in ta/me</td>
<td>.1003</td>
<td>2.70*</td>
<td>-.1492</td>
<td>-.78*</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Exp-Associated</th>
<th>Rec-Associated</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adjusted r²</td>
<td>.115</td>
<td>.130</td>
</tr>
<tr>
<td>F</td>
<td>6.28*</td>
<td>6.83*</td>
</tr>
<tr>
<td>Chi-sq(No-ind)</td>
<td>124.34*</td>
<td>233.18*</td>
</tr>
<tr>
<td>Chi-sq(Ind)</td>
<td>76.53</td>
<td>114.39*</td>
</tr>
<tr>
<td>F-Ind. var.</td>
<td>3.07*</td>
<td>5.97*</td>
</tr>
<tr>
<td>N</td>
<td>1134</td>
<td>975</td>
</tr>
</tbody>
</table>

* indicates the coefficient is significantly different from 0 at the .05 level.
^ indicates the coefficient is significantly different from 0 at the .10 level.
F-Ind Var. refers to the F test used to detect significance of the expanded model that included industry dummy variables over the reduced, "accounting ratio only" model.
Chi-square (No-ind) is the test statistic for dependency tests of the contingency table 4xn, where n is the number of industry codes (4-digit) and 4 represents the residual quartile levels from regressions with no industry controls.
Chi-square (Ind) is same as above with industry controls added.
6.3.1.7 Summary of Multiple Regression Tests of Hypothesis (1)

The multiple regression tests presented in this section generally confirm the earlier simple regression findings. In the recession-sensitive STEPWISE "best" model derived from the variables of Table 9, Panel A, all of the model variables exhibited consistent significant shifts in association across BVCP type except for change in working capital (#67). Subsequent analyses to control for various econometric problems tended to confirm these findings, though significance levels in the reduced observation subsets did not permit statistical confirmation for every variable in all analyses. In addition, operating profit to sales (#35) and change in pre-tax income to sales (#38) exhibited incongruent results in these later tests, suggesting that the association shift that was detected for these variables may be the result of model mis-specification. Additionally, change in inventory (#11) was negative across both BVCP types in these further tests (though the coefficient was insignificant in almost all cases when the model was estimated with expansion-associated BVCP data). When all 4 digits of the industry code were controlled, however, this variable was significantly negative across both BVCP types, suggesting that any detected shift was again spurious and the result of model mis-specification.
Strength of association for this model, as proxied by adjusted $r^2$, was consistently stronger when recession-associated BVCP data were used to estimate the recession-sensitive model. This also is congruent with the earlier simple regression findings.

In the expansion-sensitive STEPWISE "best" model derived from the variables of Table 9, Panel B, all of the model variables exhibited consistent significant shifts in association across BVCP type. These shifts were congruent with the findings detected in the earlier simple regression analyses. Subsequent analyses generally supported the conclusion that hypothesis (1) can be rejected for these variables. Again, significance levels in the reduced-observation data sets did not always permit confirmation in all analyses. Further, operating profit to sales (#35) again produced inconsistent results in later tests, particularly those that controlled for industry effects.

6.4 TESTS OF HYPOTHESES (2A) AND (2B)

This section presents the results of tests of prediction accuracy of the two "best" STEPWISE models derived from the variables in Table 9, Panels A and B. The purpose of these tests is to provide further evidence that accounting ratio associations with subsequent BVCP SARs shift across BVCP type.

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The prediction tests presented here are more rigorous than the analyses presented in the previous section because magnitude, as well as direction (i.e., coefficient signs), of associations across BVCPs must be robust. These tests can thus determine to what extent the detected association shifts may affect the PDU of accounting data when these are used in simple linear regression models.

These tests, formally of hypotheses (2a) and (2b), proceeded as follows. Each of the two models was estimated with pooled BVCP data of a given BVCP type. The recession-sensitive model (derived from the variables of Table 10, Panel A) was estimated with pooled recession-associated BVCP data. Similarly, the expansion-sensitive model (derived from the variables of Table 10, Panel B) was estimated with pooled, expansion-associated BVCP data. The resulting prediction models were then used to predict subsequent BVCP SARs for future holdout periods. The recession-sensitive STEPWISE "best" model was used to predict three holdout periods: the next BVCP that was the same in BVCP type as the data used to estimate the model (1981-1982); and two dissimilar BVCP periods, one preceding (1975-1980) and one following (1982-1987) the similar BVCP holdout sample. The expansion-sensitive STEPWISE "best" model was used to predict SARs for two holdout periods: the next BVCP that was the same in BVCP type as the data used to estimate the model (1982-1987); and a dissimilar
BVCP period that preceded the similar BVCP holdout sample (1981-1982).

Prediction errors were then computed and averaged. The average prediction errors were then compared across holdout sample BVCPs for accuracy. If association shifts occur as a function of BVCP type, the most accurate predictions should occur when the holdout period and the estimation model are matched by BVCP type. Predictions and errors were made and analyzed for full unscreened datasets, datasets with outliers deleted, and datasets with low sales and high growth firms deleted; and for models with industry controls included.

Results for the recession-sensitive model are presented in Table 19, Panel A. The only detectable shift in prediction accuracy for the model appears to be associated with time dependency. The prediction periods that are farther away in time from the estimation period exhibit greater average error than those closer in proximity to the estimation periods. Only one significant model demonstrated strongest prediction accuracy when estimation and prediction BVCPs are similar. This was the model with no deletions. Subsequent Duncan's and Fisher's LSD multiple range tests, however, showed that the mean prediction error for the similar BVCP period was insignificantly different from that of either or both of the other, dissimilar BVCP holdout samples.
Further analysis of the standard deviation of errors cross sectionally for each sample again demonstrates no clear trend for the recession-sensitive model. The results, taken together, suggest that hypothesis (2a) cannot be rejected for the recession-sensitive STEPWISE "best" model. The PDU of these accounting ratios, when used to make specific linear forecasts of future SARs, does not seem to vary systematically across BVCP type.

Results for the expansion-sensitive model are presented in table 19, panel B. Here, a trend is detected that suggests prediction accuracy is stronger when estimation and prediction BVCPs are similar. Note, however, that the differences, while significant in all cases, are quite marginal (the original SAR values were standardized and scale-free so that a .05 difference in error is quite small in magnitude) across the various models.

The standard deviation of error for the two groups is clearly smaller in all cases when BVCPs for the prediction and estimation data are similar. These findings, taken together, suggest that hypothesis (2b) can be rejected: the BVCP type of the holdout period does affect the PDU of accounting data when the expansion-sensitive STEPWISE "best" model is used, together with pooled, expansion-associated BVCP data.
Table 19
Panel A
Multiple Regression Results
The Stepwise Model Developed From
Consistently Associated Accounting Ratios
in Recession-Associated BVCPs
*Tests of Prediction Accuracy in Holdout BVCPs*

<table>
<thead>
<tr>
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<th></th>
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</thead>
<tbody>
<tr>
<td>None</td>
<td>1781</td>
<td>No-Ind</td>
<td>.07</td>
<td>-.04</td>
<td>-.14</td>
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</tr>
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<td>High Growth, Low Sales</td>
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<td>Ind-A</td>
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<td>-.20</td>
<td>6.51*</td>
</tr>
<tr>
<td>High Growth, Low Sales</td>
<td>1344</td>
<td>Ind-B</td>
<td>-.14</td>
<td>-.07</td>
<td>-.09</td>
<td>.68</td>
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</tbody>
</table>
Table 19
Panel A (Cont.)
Multiple Regression Results
The Stepwise Model Developed From
Consistently Associated Accounting Ratios
in Recession-Associated BVCPs
*Tests of Prediction Accuracy in Holdout BVCPs*

<table>
<thead>
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</thead>
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<tr>
<td>None</td>
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<td>1.01</td>
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<td>.94</td>
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<tr>
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<td>.94</td>
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<tr>
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<td>Ind-B</td>
<td>.90</td>
<td>1.00</td>
<td>.97</td>
</tr>
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</table>
Table 19
Panel B
Multiple Regression Results
The Stepwise Model Developed From
Consistently Associated Accounting Ratios
in Expansion-Associated BVCPs

*Tests of Prediction Accuracy in Holdout BVCPs*

<table>
<thead>
<tr>
<th>Data Excluded</th>
<th>N</th>
<th>Model Type</th>
<th>Mean Error Rec, 1981-1982</th>
<th>Mean Error Exp, 1982-1987</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
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<td>No-Ind</td>
<td>-.14</td>
<td>-.04</td>
<td>7.17*</td>
</tr>
<tr>
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<td>.06</td>
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<tr>
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<td>Ind-A</td>
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<td>Ind-B</td>
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<td>.05</td>
<td>6.53*</td>
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</tbody>
</table>

Ind-A refers to the regression with controls added for first digit of industry code.
Ind-B refers to the regression with controls added for four digits of industry code.
Table 19  
Panel B (Cont.) 
Multiple Regression Results  
The Stepwise Model Developed From Consistently Associated Accounting Ratios  
in Expansion-Associated BVCPs  
*Tests of Prediction Accuracy in Holdout BVCPs*  

<table>
<thead>
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</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>1725</td>
<td>No-Ind</td>
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<td>No-Ind</td>
<td>.90</td>
<td>.81</td>
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<tr>
<td>High Growth, Low Sales</td>
<td>1438</td>
<td>Ind-A</td>
<td>1.01</td>
<td>.87</td>
</tr>
<tr>
<td>High Growth, Low Sales</td>
<td>1231</td>
<td>Ind-B</td>
<td>1.00</td>
<td>.87</td>
</tr>
</tbody>
</table>

Ind-A refers to the regression with controls added for first digit of industry code.  
Ind-B refers to the regression with controls added for four digits of industry code.
6.5 POSSIBLE EXPLANATIONS FOR THE RESULTS

This study has disclosed that several accounting-based ratios' associations with subsequent firm returns vary systematically across BVCP type. These results were found to be generally robust for the following accounting-based ratios: (1) change in depreciation, (2) depreciation over plant assets, (3) change in inventory, (4) dividends over total assets, and (5) change in total assets over market equity. In addition, two profitability measures--operating profit to sales and change in pre-tax income to sales--exhibited systematic variation in association with subsequent BVCP SARS across BVCP type.

The findings with respect to the profitability measures were not robust, however. For these variables, associations with subsequent BVCP SARS failed to vary across BVCP type in several subsequent tests designed to detect robustness (unpooled regressions, outlier-deleted samples, and regressions with added controls for 4-digit industry code). This section offers possible explanations for the summary findings reported here.

Many of the variables that are systematically associated with recession-associated BVCP SARS are negatively signed. Those variables include: (1) changes in inventory, (2) change in depreciation, (3) depreciation over plant assets, (4) and change in total assets over market equity (a leverage
measure). The negative associations found for these types of variables suggest that accounting ratio data may detect fundamental differences in management strategies and perceptions. Optimistic managements pursuing growth strategies may experience the lowest SARs in subsequent recessionary cycles. For example, an optimistic management may take on debt and invest heavily in research and development, inventory and/or new assets during the year(s) prior to the onset of recession. This would result in positive rates of change for inventories, depreciation and depreciation over plant assets. If recessionary conditions then develop (ex-post), these tactics become disadvantageous. If the optimistic strategies are intractable in the sense that they are not easily reversible, lower recession-associated BVCP SARs would then be expected to result. Accounting data may thus capture some of management's intentions and tactics, increasing PDU to investors. Examining this behavioral notion is one possible extension of this study for future research.

A further result of interest concerns the variable associations that relate to profitability. In general, these variables (operating profit to sales, pre-tax income to sales) are positively associated with recession-associated BVCP SARs and negatively associated with subsequent expansion-associated BVCP SARs. The magnitudes of association are fairly symmetric. This may imply that profitability measures capture a portion

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of systematic sensitivity to recession and expansion that beta estimates and firm size do not. On the other hand, the fact that the findings for these variables were not robust in several follow-up tests suggests that confounding events and/or sample-specific outliers may have caused the variation in association across BVCP type.

Finally, certain variables that relate to firm structure were significantly associated with subsequent BVCP SARs. For example, dividends to total assets were positively associated only with subsequent recession-associated BVCP SARs. High yielding stocks with low growth potential but steady income streams are widely believed by many in the investment community to be good defensive issues in recession-associated BVCPs. This research seems to confirm this.

Another result of interest is that many more variables are associated with subsequent recession-associated BVCP SARs than with expansion-associated BVCP SARs. This may be caused by the fact that recessionary conditions are sharper, more painful, and require more firm-specific actions in order to contend with them. Another possible explanation is that accounting data, because of the accounting principle of conservatism, are more sensitive to events that may lower assets valuations and/or revenue streams (i.e., recessions). For example, conservative accounting valuation methods, such as the lower of cost or market, may effectively limit RESULTS
expansion-associated valuation information while providing unconstrained recession-associated information to investors. Further research is needed to explore this and other possible causes for the different levels of accounting data sensitivity that were detected across BVCP type.
CHAPTER 7

CONCLUSION

7.1 SUMMARY OF FINDINGS

This study examined two basic questions. First, do accounting ratio associations with subsequent abnormal returns vary systematically across business-cycle associated valuation change periods (BVCPs)? Second, is the predictive decision usefulness (PDU) of accounting data, as proxied by predictive accuracy, affected by business cycle events?

To address these questions, an interaction theory was presented that posits the existence of an interaction between accounting ratio associations to subsequent abnormal returns and the operative business cycle event. To find evidence of the existence of this interaction, a large set of accounting ratios was examined in the context of simple regression to determine if ratio associations to subsequent abnormal returns did vary systematically across BVCPs. The results showed that several ratio associations did vary. Multiple regressions were then tested to confirm these findings and to examine various possible model mis-specifications that may have caused spurious findings.
7.1.1 Conclusions Concerning the Existence of Association Shifts Across BVCP Type

The simple regressions disclosed that several variables' associations with subsequent BVCP abnormal returns vary consistently across BVCP type. These findings were confirmed using multiple regressions of several variables. In particular, change in depreciation and depreciation over plant assets were negatively associated with the subsequent abnormal returns (SARs) of recession-associated BVCPs. These were positively associated with subsequent expansion-associated BVCP SARs in all tests. Change in inventory also exhibited a similar pattern, but this was not confirmed in all tests.

Change in dividends to total assets was positively associated with subsequent expansion-associated BVCP SARs in all tests. This variable shifted in direction of association across BVCP type, becoming negatively associated with subsequent recession-associated BVCP SARs. Two other variables--operating income to sales and change in pre-tax income to sales--exhibited a similar shift across BVCP types, although the results were not confirmed by all tests.

Finally, change in total assets to market equity, in all analyses, was positively associated with expansion-associated BVCP SARs and negatively associated with subsequent recession-associated BVCP SARs.
Collectively, these results indicate that abnormal return associations of accounting ratios can shift solely as a function of business cycle events occurring in time. The strengths of these associations, as measured by adjusted $r^2$, were also much stronger when recession-associated BVCP data were used in model estimations.

These findings, taken together, have broad ramifications for empirical research involving these variables. In particular, studies that use cross-sectional data pooled across time may detect significant abnormal return associations that are the result of model mis-specifications with respect to business cycle events. This is true especially when studies use data pooled across time periods that include recession-associated BVCPs. The strong association shifts occurring in these periods may cause spurious significant findings.

For example, in the study by Ou (1990), some of the variables determined here to be sensitive to BVCP type survive Ou’s screening process and enter prediction models. In particular, change in dividends to total assets, change in inventory, change in depreciation, and measures of operating profit, such as return on equity, enter Ou’s prediction model. Ou finds that these variables add incremental predictive power over current earnings when applied in her LOGISTIC model. Ou’s
sample is derived using data pooled over the time period 1965-1977. This period includes two recession-associated BVCPs. The 
Ou finding may therefore be interpreted to be the result of 
model sensitivity to BVCP type, as opposed to notions that 
accounting numbers filter out transitory earnings elements, 
such as proposed by Ou and Penman (1989b). Of course, the 
model used in this study is the more simplistic linear model, 
and several variables are rank transformed or standardized. 
The findings here may not necessarily replicate in a LOGISTIC 
application. Nevertheless, it is interesting that Ou’s 
results, in terms of variables that survive, are so closely 
congruent to the findings here. Similar comments can be made 
for the original Ou and Penman study (1989), because data were 
again pooled across several BVCPs. While not reversing the 
original finding, the results here, if generalizable to 
LOGISTIC applications, suggest that the Ou and Penman findings 
may be at least partly the result of ratio sensitivity to 
BVCPs. The positive return results from the zero net 
investment position in Ou and Penman (1989a) may therefore not 
imply market inefficiency, with respect to information 
contained in accounting numbers, as has been suggested (Ou and 
7.1.2 Conclusions Concerning the PDU of Accounting data

As to the second and more difficult question of the BVCP effect on accounting data's PDU to investors, the results are more ambiguous. The recession-sensitive model, using recession-associated BVCP data for estimation, produced better predictions in recession-associated BVCP holdout periods than in expansion-associated periods, but the result was not replicated in any of the samples and models that controlled for outliers and cross-sectional model misspecification. The expansion-sensitive model did demonstrate, in all cases, significantly better prediction when BVCPs for the estimation and holdout data were of the expansion-associated type.

The evidence here suggests that, although association shifts are occurring across BVCP type, the PDU of accounting numbers may not be greatly affected by BVCP events, at least when linear regression models are used for prediction. This result has been found before in the case of unconditional (with respect to events) models (Nerlove, 1968; and O'Conner, 1973) and is not surprising. In fact, the poor ability of accounting data to make correct, exact predictions of subsequent returns probably led to the subsequent search for various alternative return prediction approaches, including
rank predictions (O'Connor, 1973) and LOGISTIC modeling (Ou and Penman, 1989).

The assumption of semi-strong efficient markets implies that accounting numbers should not systematically predict subsequent returns in models that do not condition on pre-knowledge of cyclical events. For these models, a negative finding in the empirical research, especially for the prediction of abnormal returns, is therefore expected and consistent with the paradigm of market efficiency.

The case however for models conditioned on pre-knowledge of events is very different, however. In order to reach an efficient valuation consensus, investors must assess the effects of different states of nature, including business cycle events. If, for example, a recession occurs, what will happen to asset values and subsequent portfolio returns? This form of PDU for accounting data may exist even if markets are efficient and nobody can systematically predict future business cycle events. The question of whether accounting data have PDU in models that condition on events is thus portentous to the very forces that make markets efficient (as investors form probabilistic assessments of the future and then determine and efficiently weigh the expected effects of such conditions). So far, in this research, the evidence indicates that accounting data do not contain substantial PDU with respect to business-cycle events, when applied to making exact predictions in

CONCLUSION
linear regression models. The alternative of non-linear models, trading rule strategies, and rank predictions follow as integral steps in this research to further explore this issue.

7.1.3 Conclusions Concerning Transformation Procedures

Finally, this research has examined various transformations of accounting data. The study confirms previous findings that log and square root transformations, as well as squares and cubes, do not generally increase accounting data’s association to returns. The study also examined standardization and rank transformations of variables. The preliminary results indicate that these data-reduction transformation techniques, particularly ranking procedures, may have a profound positive impact on accounting ratio associations with subsequent returns.

The notion that rank transformations improve accounting ratio/return associations is quite intuitive and congruent with known financial statement analysis techniques (which use comparative within-firm and industry benchmark ratio values) and empirical research procedures that use portfolio group designs. As such, it is really a very classical notion. The innovation here is the use of relative rank transformations (deflated by the number of observations being ranked) in a general cross-section without grouping. The resulting CONCLUSION
transform retains relative inter-firm information while reducing distance data defined from essentially meaningless absolute values. A great deal of noise appears to be filtered out of the original variable. The techniques seem to improve the use of accounting numbers in linear models and thus represents a contribution to the transformation research literature.

7.2 LIMITATIONS OF THE STUDY

The study is constrained by a number of possible limitations. First, while the study did attempt to control for several omitted variables and model mis-specifications, the inherent weakness of any non-experimental design to fully control for correlated variables limits the conclusions to the level of simple association. It is possible that BVCPs are correlated with other confounding events or cross-sectional factors that were not controlled or tested in the study.

Another problem imposed by the nature of the events is the very limited number of BVCP sub-periods for each BVCP type. It is plausible that some confounding event has repeated across the similar BVCP intervals, thereby leading to a spurious conclusion that BVCPs are driving the result. This seems unlikely, given the great differences in conditions.

70 Meaningless in the sense that there is no current theoretic interpretation of the values.

CONCLUSION
across the BVCPs that were found. Nevertheless, the limited number of sub-periods leaves this possibility open and will require replication work as new BVCPs emerge.

Another limitation is that the results may have been caused by history and maturation effects occurring at the time of measurement. The time-dependency design controls attempted to partially control for this problem. Again however, other effects may exist that were not examined.

A potential problem in this study is the inherent weakness and assumptions built into the use of financial ratios themselves. Accounting ratios may be affected by the inappropriate use of size deflators, the lack of provision for an intercept term or error term in the relationship depicted by a ratio, and other rigidities in such a measure, as discussed by Lev and Sunder (1979). This study has used a set of very typical financial ratios. More flexible measures might exhibit very different associations with subsequent abnormal returns. In particular, accounting ratio data may have more PDU with respect to associations across BVCP type if less noisy measures of account relationships are used. This problem should understate the associations that were found, however, and make the association shifts potentially greater than what was detected in this study.

Similarly, there is the difficulty of pooling data over time and firms. If the various ratio characteristics are
associated differently across firms and firm groups, the detected associations of ratios with subsequent BVCP SARs will be measured with error. To some extent, the industry controls and cross-sectional influence tests of model mis-specification control for this limitation. Any undetected differences in cross-sectional association would add noise to the results, thereby tending to understate any findings.

Another limitation is the survivorship bias and sample selection bias created by the data demands of the study. Because full data for each variable in a model were required for inclusion of that observation, the sample necessarily did not represent a random sample of firms taken from the whole population. In particular, banks, utilities, and service firms were not well represented. It is possible that very different associations occur in these other groups. The findings are therefore limited as to generalizability. Similarly, the requirement of full data across a BVCP inevitably caused a screening of firms that did not survive throughout the BVCP. This could have biased the results, particularly in recession-associated BVCPs where bankruptcies and general business failures tend to increase.
7.3 SUGGESTIONS FOR FUTURE RESEARCH

This study can be extended in several new directions of interest. First, non-linear approaches, such as ranking and probabilistic binary modeling (i.e., PROBIT and LOGIT) can be designed and examined to determine if the PDU of accounting data is further affected when these models are employed.

In addition, zero net investment trading rules can be implemented to determine the extent to which foreknowledge of business cycle events is useful in investment strategies that depend on fundamental analysis. As noted earlier, a great deal of attention and resources are dedicated to the detection of recurring business cycle events. If firm-specific PDU of accounting data is largely unaffected by this foreknowledge, more simplistic hedging strategies may be possible.

Another direction of interest concerns other time-series mis-specifications. The literature is replete with examples of cross-sectional mis-specifications such as size, industry effects, etc., that may cause spurious findings. On the other hand, there has been far less attention given so far to the problem of time series dependencies in accounting numbers. A great deal remains to be learned in this area. Techniques such as those applied in this study can be replicated for other potential confounding events.

CONCLUSION
Finally, our understanding of severe business cycle changes is just beginning. Only two truly severe business recessions have occurred in the post-war experience (1973-1974 and 1981-1982). Little is understood about why certain variable associations vary across BVCP type events while others do not. Why, for example, are change in depreciation and depreciation over plant assets, representing heuristic allocation mechanisms, sensitive to BVCP type? On the other hand, why are more direct event measures, such as some of the profitability ratios, not sensitive? Why is change in dividends over assets positively associated with subsequent recession-associated BVCP abnormal returns and negatively-associated with subsequent expansion-associated abnormal returns? Why are accounting data associated much more strongly with subsequent abnormal returns in recession-associated BVCPs? These questions await further inquiry and study as logical extensions of this research.
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VITA

Gregory D. Kane was born on October 22, 1953 in Baltimore, Maryland, the son of Clarence John Kane and Virginia Ruth Kane. In 1971, he graduated from Northern High School.

From 1971-1973, he began study at Essex Community College, in Baltimore, MD, towards the Bachelor of Arts degree. He also gradually developed an interest in business and sales. From 1973-1975, he worked as an insurance agent, selling all lines of personal and business insurance. From 1975-1976 he continued study towards the Bachelor of Arts degree by attending the University of Maryland, Baltimore County. In 1977, he began to sell residential real estate. In December, 1979, he accepted a position as Vice-President of residential sales for Kayhouse Realty, Inc.

In November, 1981, he joined the management of The Baltimore Sun, in the capacity of sales manager, where he was ultimately placed in charge of all out-of state circulation. He remained at the paper until November, 1987. While at the Baltimore Sun, from 1985-1987, he attended Shepherd College in
Shepherdstown, West Virginia. In December, 1987, he graduated and received the Bachelor of Arts degree from Shepherd College.

The following year, on the first sitting, he passed the examination for Certified Public Accountant. He also accepted a position at the Bank of Charles Town, Charles Town, West Virginia, as Trust Officer, where he managed trust assets and was responsible for all trust tax filings.

In May, 1989, he began study toward the Master of Accountancy degree at Virginia Polytechnic Institute and State University in Blacksburg, Virginia. He successfully completed the program in May, 1990. He then began study toward the Doctor of Philosophy in Business Administration with a major concentration in Accounting.

He has accepted a position as Assistant Professor of Accounting at The University of Delaware, in Newark, Delaware, effective February, 1993.