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The valuation information associated with the sequence of accounting earnings

Lyon, John Douglas, Ph.D.
The Ohio State University, 1991
THE VALUATION INFORMATION ASSOCIATED WITH
THE SEQUENCE OF ACCOUNTING EARNINGS

DISSertation

Presented in Partial Fulfillment of the Requirements for
the Degree Doctor of Philosophy in the Graduate
School of the Ohio State University

By

John Douglas Lyon, B.Com.(Hons)., M.F.M.

* * * * * *

The Ohio State University

1991

Dissertation Committee:
Andrew D. Bailey, Jr.
Stephen R. Coslett
Douglas A. Schroeder

Approved by
Andrew D. Bailey, Jr.
Adviser
Faculty of Accounting
and
Management Information Systems
To my parents,
Douglas James Lyon
and Marion Lyon.
I would like to thank the following people for their help in the dissertation process and their support over these past years:

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VITA

December 13, 1954 ....................................... Born-Inverell, Australia

1977 ......................................................... Bachelor of Commerce (Hons), University of Queensland, Australia

1980 ........................................................ Master of Financial Management
University of Queensland, Australia

1980-1982 ............................................... E.D.P. Audit Manager, Kendalls,
Chartered Accountants, Australia

1982-1987 ............................................... Queensland Institute of Technology,
Senior Lecturer in Financial Accounting

1987-1991 ............................................... Graduate Teaching Associate and
Graduate Research Associate,
The Ohio State University

FIELDS OF STUDY

Major Field: Accounting and Management Information Systems

Minor Fields: Econometrics
Applied Statistics
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CHAPTER I
Introduction

The firm's financial accounting system provides a formal mechanism by which current and future stockholders are informed about the firm's continuous operations. The reporting structure consists of a mechanism to report the stock of wealth at a given time point (the balance sheet) and the increment or decrement to wealth (accounting earnings) between to time points (the income statement). This reporting mechanism is in no way arbitrary, in the sense that rules and conventions embodied in Generally Accepted Accounting Principles (GAAP) as well as various regulatory requirements, dictate how and when accountants report.

A number of prior studies have attempted to document whether earnings numbers, as the accountant's measure of value change, associate with the market valuation of firm equity. Little attention has been paid to the issue of accounting being only one of a multiple number of information sources that potentially impacts investors' beliefs about firm value. Further, little reference has been made to the unique reporting mechanism observed by accountants and whether, under different economic contexts, it may better characterize the dynamic process of firm valuation.

In this study, an empirical methodology is designed and implemented to gather evidence concerning these two issues. Specifically, given prices incorporate all valuation information, the study devises a statistical measure of the relative ability of the sequence of accounting earnings releases to characterize firm value changes on average across time. Second, it is argued that the economic context provided by firm's
production/investment circumstances dictates variation in this relative information content in the earnings sequence.

The study proceeds as follows: Prior related research is discussed with specific attention given to the shortcomings recently highlighted by a number of researchers. The contributions made by this study to this literature are then documented. The theory of valuation dynamics as proposed by Antle, Demski and Ryan [1989] is then discussed. This allows the generation of hypotheses. The study then turns to considering econometric models to gather evidence on these hypotheses. This is followed by the specific methods of implementation and analysis for these models. Finally, the results are reported and conclusions presented along with the limitations of the study and possible future extensions.
CHAPTER II
Previous Related Research

This chapter presents a review of the related research that is extended in this study. The focus of this review is the specific areas of capital markets research in accounting that raise the research questions upon which this study was motivated.¹

Five areas of research interest within accounting primarily motivated this study and are reviewed in this chapter. These are:

1. Theoretical work on how accounting as the firm’s formal reporting system about operations associates with firm valuation.

2. Empirical work that is aimed at establishing both the extent of this valuation relationship in markets, as well as the determinants of potential variation in this valuation relationship caused by forces exogenous to accounting.

3. Recent speculations in the literature that endogenous characteristics of accounting as a reporting system possibly affect the valuation relationship.

4. The speculation that economic context potentially determines the information content of a disclosure.

5. Whether informative releases affect the moments of the distribution of uncertain future returns at a given time point.

Clearly, these five areas overlap in that many studies consider both theoretical and empirical issues in motivating their analysis.

¹For a recent extensive review of capital markets research in accounting, see Bernard [1989].
Given that the empirical analysis in this study is considerably different from most prior research, the final subsection considers how the approach taken has extended the literature by addressing a number of shortcomings raised by various writers in prior empirical analyses.

2.1 Related Literature

2.1.1 Theoretical Valuation Studies

A limited quantity of research has been undertaken in creating a theoretical link between the accountant's measures of firm performance and the price of the firm's security. One possible explanation for this is that research prior to Beaver, Clarke and Wright [1979] tended to model the relationship between firms returns and some publicly disclosed piece of information based upon the predicted sign of the information content. This approach stemmed from Ball and Brown [1968] who adopted a model in which returns depend upon the sign of unexpected earnings. Beaver, Clarke and Wright [1979] was the first study in which the magnitude of the unexpected earnings component was associated with firm returns, although no particular valuation model motivated the specification of a functional relationship between returns and earnings.

Beaver, Lambert and Morse [1980], although not a theoretical study, was the first to specifically use a valuation model to motivate the method of empirical analysis. The theoretical model used was the classic dividend valuation model extensively analysed by Miller and Modigliani [1961]. This models price as the discounted present value of the firm's dividend stream in perpetuity. Beaver, Lambert and Morse [1980] adapted this model to relate it to the valuation information in accounting earnings by considering accounting earnings as an economic variable, rather than a mere source of informative signals as had been done in the research prior to 1980. The principle adaptation took the form of assuming accounting earnings to be a "garbled" measure of permanent earnings. Therefore, in so far as permanent earnings was an economic variable that told market participants something about future dividends, a direct
valuation link was created between accounting earnings as a valuation measure and firm price. The major issue in showing the valuation information in accounting earnings became the derivation of an econometric method to overcome the "garbling" or measurement error in accounting earnings—a problem induced by the way the researcher theoretically viewed accounting earnings. Methods to overcome this measurement error issue were further considered in Beaver, Lambert and Ryan [1987] and Brown, Griffin, Hagerman and Zmijewski [1987].

Although criticized by Ohlson [1989] as being underidentified with respect to the economic content of permanent earnings, and therefore largely tautological, the paper spawned a variety of empirical valuation studies based on the argument that accounting earnings told investors something about the future dividend component of valuation. Examples that will be considered below are Collins and Kothari [1989] and Kormendi and Lipe [1987].

The idea of giving economic content to accounting variables had been in the theoretical literature prior to Beaver, Lambert and Morse [1980], although the dividend valuation model has featured in most empirical research. Garman and Ohlson [1980] modeled firm prices as the equilibrium outcome of the dynamic evolution of informative variables about the firm. This dynamic process was modeled as linear in an unidentified vector of state descriptors (information variables) about future dividends. Utilizing the no-arbitrage analysis of Rubinstein [1976], and given these linearity assumptions on the state descriptors, firm price at a given time point reduced to a linear function of these information variables. Studies employing this valuation model assumed one of these information variables to be accounting variables. This provided a motivation for modeling returns as a linear function of accounting earnings and any other informative variables posited by the researcher to affect future dividends. The major empirical study motivated by this analysis has been Easton and Zmijewski [1989].
One problem with this general valuation framework posited by Garman and Ohlson was the identification of these state descriptors. Ohlson [1988] further refined the model by invoking a number of restrictions on the behavior of accounting variables and dividends. These restrictions amounted to maintaining the clean surplus valuation equation and the dividend irrelevancy propositions of Miller and Modigliani [1961]. This result has motivated a number of recent valuation studies that further explore the relationship between measures of earnings, dividends and other information. The most notable of these are Easton and Harris [in press], and Lyon and Schroeder [1991]. The major contribution of the Garman and Ohlson [1980] and Ohlson [1988] analyses, is that specific theoretical content is given to the accounting observables of dividends, earnings and book values. That is, one motivates the link between returns and accounting measures, not by reference to the illusive permanent earnings, but by direct links to the economic characteristics of accounting as a reporting mechanism. In this way accounting has endogenous characteristics that yield economic meaning, rather than its economic meaning flowing from exogenous attachment (via permanent earnings) to future dividends.

Recently, Antle, Demski and Ryan [1989] have proposed a model which, can be viewed as a general version of Garman and Ohlson [1980] and Ohlson [1988]. The similarity lies in considering accounting as one of multiple sources of information available to market participants in setting the firm’s security price. Further, this informative role of accounting is dynamic in nature as accountants continuously report economic events that frame dividend expectations. The contrast with Ohlson's work comes about by not imposing any particular functional form upon how information evolves across time. That is, the linear state dynamics commonly associated with Ohlson's work is non-existent. Instead, Antle, Demski and Ryan propose two likelihood structures about the firms liquidating dividend. The first characterizes

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2 The clean surplus equation is that at any given time point (absent capital contributions), the book value of the firm must equal the the prior periods book value plus earnings less dividends.

3 The concept of market participants valuing a liquidating dividend is merely used to simplify the analysis over a model in which dividends are paid at interim points prior to liquidation.
the value of the firm conditional on all sources of information to a point in time, the second characterizes valuation conditional on what the accounting system reports to that point in time. Contrasting these two likelihood structures based upon their observable outcomes becomes the core of the analysis. What they find is that the valuation role of accounting depends on its endogenous characteristics embodied in its rules and conventions, as well as its relationship with other sources of information. Further, they suggest that this role is likely to depend upon the economic context in which the firm operates. The theoretical underpinnings of Antle, Demski and Ryan’s [1989] work form the theoretical basis of this study and are extensively reviewed in Chapter III.

2.1.2 Empirical Valuation Studies

As discussed in the previous subsection, the contribution of Beaver, Lambert and Morse [1980] was to model firm returns as a linear function of the magnitude of unexpected earnings. The major result of the study was to conclude that earnings are a dated source of information in that their findings suggest that prices lead earnings.4 Their methodological contribution came from providing a theoretical basis for the contemporaneous regression of a measure of unexpected earnings on firm returns. What followed was a host of studies employing this methodology, with the regression coefficient on unexpected earnings being dubbed the earnings response coefficient (ERC).

Regressions of this nature have been used to investigate two quite different aspects of information content. The first looks at the surprise in the market place of a given earnings announcements over a relatively short period of time. These are classified as event studies. The second considers how well earnings captures economic events that are captured in stock prices (usually) on an annual basis. These are classified

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4Collins, Kothari and Rayburn [1987] directly extended this results to show that prices lead earnings to a greater extent for large firms. Beaver, Lambert and Ryan [1987] introduced reverse regressions as an alternative econometric technique to that offered in Beaver, Lambert and Morse [1980].
as *association* or *valuation* studies. Collins and Kothari ([1989], p144) draw this distinction:

Generally, the return/earnings relation is investigated using either an "event" study or an "association" study method. The event studies infer whether the *earnings announcement*, per se, causes investors to revise their cash flow expectations as revealed by security price changes measured over a short time period (typically, 2-3 days) around the earnings announcement. ... In an association study, returns over relatively long periods (fiscal quarters or years) are regressed on unexpected earnings ... over a forecast horizon that corresponds roughly with the fiscal period of interest. Association studies recognize that market agents learn about earnings and valuation-relevant events from nonaccounting information sources throughout the period. Thus, these studies investigate whether accounting earnings measurements are consistent with the underlying events and information set reflected in stock prices. Typically, causality is not inferred. Rather, the focus is on whether the *earnings determination process* captures in a meaningful and timely fashion the valuation relevant events.

Unfortunately, the literature uses the term "earnings response coefficient" in the context of regressions performed with these two quite different research objectives in mind.\(^5\) The concern in this dissertation is with those studies that can be classified as association or valuation studies (although studies of an event nature tend to predominate). The most influential of these have been Collins and Kothari [1989] and Kormendi and Lipe [1987], with extensions to these original works taking place in Kothari and Sloan [1990] and Lipe [1990].

Largely motivated by the work of Miller and Rock [1985] and Kormendi and LaHaye [1986], Kormendi and Lipe [1987] investigated the extent to which the impact of a current earnings innovation on stock prices varies according to how much of the current earnings innovation will persist in future earnings streams. They found support for this notion of earnings persistence in that some degree of period by period dependence in the assumed time series process of earnings was associated with returns.

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\(^5\) Easton and Zmijewski [1989] also use the term "earnings response coefficient" although they explicitly state that (p177), "This paper focuses on the coefficient relating the surprise (new information) in accounting earnings to abnormal stock returns."
One way to interpret these results in the context of this study is that it provides evidence consistent with a dynamic information environment in which the information content of earnings derives from conditioning on previous earnings numbers. In other words, observing that earnings persist suggests that some form of conditioning on prior earnings takes place in associating earnings with returns.

Collins and Kothari [1989] hypothesized, based on an adaptation of the classic valuation model and assumptions about the time series process of earnings, that the association between accounting earnings and returns should vary both cross-sectionally and inter-temporally. The factors affecting this association were the persistence of earnings, risk, firm growth and interest rates. The first three factors were argued to exogeneously determine cross-sectional variation in the ERC, while the fourth factor exogenously determined inter-temporal variation in the ERC. To test this cross-sectional variation they used firm size as a proxy for the information environment of the firm. Their results largely confirm their hypotheses and provided empirical support for the notion that earnings potentially has different informational association with earnings depending upon how these factors exogenous to accounting play a role in determining its valuation implications.

The primary criticisms of using the ERC methodology in association studies come from Bernard [1989] and Lev [1989]. The former author argues that regressions of this nature are likely to suffer from a severe omitted variables problem in that many other informative variables potentially explain price changes. Further, none of these variables are usually controlled for by merely regressing returns on unexpected earnings. That is, it is hard to know whether the factors that explain ERC's do so because of the valuation information in earnings, or because earnings correlates with some other omitted factor.
Similarly, Lev [1989] criticizes studies of this nature for the low explanatory power in terms of $R^2$, and calls for a change in direction of this line of research.\footnote{The usual level of $R^2$ reported in studies of this nature as documented by Lev [1989] is of the order of 3 to 5 percent.}

There are two other notable features of the typical ERC study that are relevant in the context of this dissertation. First, the valuation information in earnings measured by the contemporaneous regression is only concerned with associating the mean of returns with earnings. Accounting as an information source is assumed to have no affect upon investors assessments of the variance of returns or other higher moments. Second, accounting earnings is treated as a somewhat abstract source of contemporaneous informative signals about value. No consideration is ever given to how accounting reports information and whether its endogenous characteristics affect its ability to convey valuation information. Related to this point is that the measurement of valuation information takes place by viewing information content as deriving from the individual releases of earnings numbers, rather than these earnings numbers comprising part of a continuous dynamic process of valuation. That is, the focus is on the information content of the individual earnings signals rather than accounting as a continuous source of valuation information. This necessarily involves considering the dynamic nature of information content, which is explored more fully in Chapter III.

2.1.3 Information Content and Economic Context

In a critical review of capital markets research in accounting, Bernard [1989] argues that little attention has been given to the economic context in which an accounting disclosure takes place in assessing its information content. This observation stems from Bernard and Stober [1989] in which the purpose was to reassess the findings of Wilson [1987]. Wilson [1987] investigated whether, for a given level of earnings, the market reacts more favorably the larger (smaller) are cash flows (current accruals). His results largely supported this contention. However, Bernard and Stober [1989] find this result to vary depending on the chosen period of calendar time. One possible
reason they conjecture for their results is that an increase in current accruals may represent either "good news" or "bad news" depending on whether it signals an increase in anticipated future demand, an unexpected decrease in current demand, or problems in collecting receivables. Given that the economic circumstances of the firm affect these situations, they conjecture that economic context is relevant in assessing information content.

Although the studies of Bernard and Stober [1989] and Wilson [1987] do not directly relate to the valuation problem addressed in this study, Bernard [1989] raises as a general proposition the idea that economic context potentially drives information content, and that this caveat has been largely missing from accounting market studies. He goes on to speculate that this lack of consideration of economic context in designing market experiments has led to possibly erroneous conclusions about the information in various disclosure due to "averaging" effects across contexts. Similarly, Beaver, Eger, Ryan and Wolfson [1989] choose to study information content of accounting disclosure in a specific industry, arguing that "heterogeneity in production functions across firms often makes it difficult to aggregate sample evidence in a meaningful (and statistically powerful) way" (Beaver, Egar, Ryan and Wolfson [1989], p231). Finally, Antle, Demski and Ryan [1989] speculate within the framework of their valuation model, that the relationship between accounting and how it portrays economic events (accounting structure) and other information sources is potentially context dependent. That is, accounting structure plays a role in determining information content in the presence of multiple information sources under different economic contexts.\footnote{\textsuperscript{7}Chapter III further considers these speculations of Antle, Demski and Ryan in motivating the hypotheses of this study.}

2.1.4 Information Content and Return Moments

As noted in subsection 2.1.2, the conventional methodology in association (valuation) studies employs a contemporaneous regression of unexpected earnings on firm returns. Consequently the methodology implicitly attempts to measure whether unexpected
earnings at a given time point associate with (or explain) the location (or mean) of investor’s beliefs about price changes. Clearly, other moments of the firm’s return distribution are also potentially impacted by information, although no empirical study to date considers the effect of earnings upon these moments in a valuation setting. In a theoretical setting, Antle, Demski and Ryan [1989], model information content as also deriving from changes in the conditional moments of the firm’s return distribution, and it is this approach that is ultimately operationalized in Chapter IV.

In event study settings, the informational impact of earnings announcements on higher moments has been considered. Beaver [1968] documents that the variance of stock price changes is increased in the week of the earnings announcement, suggesting a revision of beliefs by investors at that time. McNichols [1988] extends this work by investigating the skewness of return distributions at earnings announcement dates versus non-announcement dates. She finds that the proportion of extreme negative to extreme positive stock price adjustments is greater at announcement dates than at randomly sampled non-earnings announcement periods. This is argued as evidence consistent with the suggestion that managers use discretionary disclosure practices in disclosing good earning’s news early, while delaying the release of bad earning’s news.

These two empirical studies appear to be the major contributions in testing hypotheses about the firm’s return distribution and the impact of information upon higher moments—but only in event time. As the next subsection reveals, extensions in this area are seen as a contribution of this study.

2.2 Extensions to the Previous Literature

This subsection outlines the extensions to the empirical valuation literature undertaken in this study. As Chapters IV and V indicate, the methodology is substantially different from that seen in prior valuation work. This largely results from the documented shortcomings in the prior subsection, but was also motivated by the ability to step
outside the conventional return/earnings framework offered by the theoretical framework of Antle, Demski and Ryan [1989]. This is extensively considered in Chapter III.

The study extends the literature in four related ways. These are:

1. By centering the analysis on accounting as a continuous source of conditioning information that potentially alters investors' beliefs about firm value, the focus turns to isolating the valuation information in the temporal process of reporting accounting earnings. This contrasts with the previous valuation literature in that the analysis is always focused upon isolating the informational impact of individual earnings releases in the period of the release via a contemporaneous regression. Such an approach assumes that all information content potentially derives from the earnings release at a given point in time, and ignores its conditioning role in the sequence of informative signals. Therefore, in this study, the focus is switched to the entire sequence or dynamic process of earnings dissemination and its valuation implications.8

2. The continuous conditioning of investors' beliefs with information is assumed to impact all aspects of uncertainty with respect to future price changes. In other words, information jointly impacts all moments of the firm's return distribution. Therefore, observing conditional variation in return moments is the outcome of expectation revision conditional on the sequential release of information. As a result, the study broadens the concept of locating information content beyond its association with the mean of firm returns. Information potentially associates with the revision of investors' beliefs about the variance of firm returns, their skewness or kurtosis.

3. To locate the valuation information in accounting earnings, the study recognizes that the observed return process is the equilibrium outcome of market

8This issue follows from the Antle, Demski and Ryan's [1989] critique of conventional valuation studies, and is extensively considered in Chapter III.
participant's conditional processing of all informative signals from multiple information sources. Accounting earnings is but one of these sources. Therefore, the analysis focusses on "unravelling" the relative valuation information in accounting earnings implicit in stock price changes. Considering relative information content is largely driven by the omitted variables criticism of conventional valuation studies. Rather than attempting to identify what these omitted valuation relevant variables might be and incorporating them in a contemporaneous regression, the focus shifts to considering relative information content based on the informational interpretation of the return process discussed in item 2 above.

4. The relative valuation information in accounting earnings, is hypothesized to depend on the economic context. In this study, the economic link is made between how accounting reports economic events and the production/investment environment in which it operates. In short, the study recognizes that the endogenous characteristics of accounting as an information system potentially affect its relative information content. This is seen as extending the empirical valuation literature in accordance with the speculations of Bernard [1989] and Antle, Demski and Ryan [1989].

In summary, this chapter has reviewed the current theoretical and empirical thought on accounting as a source of valuation information. A number of empirical shortcomings were identified. These stemmed from a number of restrictive assumptions about the information environment in which accounting operates, and a variety of econometric shortcomings resulting from these assumptions. This study is seen as contributing to the literature by relaxing many of these restrictive assumptions, and, in so doing, considering a relatively different econometric approach to valuation studies.
CHAPTER III
Theory Development and Hypothesis Generation

This chapter formalizes the thinking about dynamic information settings in general, and, given this setting, how the characteristics of accounting as one informative source dictate its relative valuation impact. The theoretical framework of Antle, Demski and Ryan [1989] (hereafter ADR) is adopted. This is done because their analysis is specifically constructed to contrast accounting with multiple information sources in a setting that allows information content to derive from the interplay of potentially informative signals across time. The major implication of their work is that the timing conventions and the restricted domain of accounting as an information source are endogenous characteristics of accounting that potentially drive its information content, and so affect its mapping to security prices.

The chapter has three parts. First, the basic structural components of the ADR analysis are outlined. Because the notion of information content in dynamic settings is central to the study, a discussion of the definition of information content and the more complex problem of locating information content in dynamic settings then follows. Finally, the accounting information source and its information content is considered. This leads to hypotheses motivated by the contextual nature of accounting information content in a dynamic setting.

9Throughout the remainder of the study, the terms “information content”, “valuation information” and “valuation impact” are used interchangeably.
3.1 Theoretical Structure

The basic construct of the ADR setting is of an information source $\eta$ which at each time point $t \in T$ releases informative signals $y_t$ about a firm's liquidating dividend $d$. The sequence of realized signals at time point $t$ is denoted $\bar{y}_t = (y_1, \ldots, y_t)$ and at each time point $t$, the sequence of realized information signals yields a probability measure concerning the liquidating dividend at time point $T$. This probability measure is denoted $\pi(y, d|\bar{y}_t)$. Its importance is in capturing the notion that at any time point $t$, all future possible signals $y$ or values of the liquidating dividend $d$ are probabilistically conditional on all prior informative signals about the firm. This is a simple formalization of the intuition that what is expected to happen in the future is probabilistically dependent on everything known about the past. Markets are seen therefore as informationally efficient. Firm value at time $t$ is the conditional expectation of the liquidating dividend discounted at a constant interest rate ($r > 0$). That is:

\[ V_t(\bar{y}_t) = E_{\pi}(d|\bar{y}_t)(1 + r)^{t-T}. \]  

(1)

The important point is that the entire sequence of information releases to time point $t$, $\bar{y}_t$, conditions liquidating dividend expectations and determines firm value. Inter-temporal observations of firm value are therefore viewed as the outcome of a stochastic process that is dependent upon the dynamic conditioning of of $\pi$ as the sequence of informative signals about the liquidating dividend is released through time.

Accounting is one information source and is denoted $\eta^a$. That is, in analagous fashion to the above, an accounting reporting history $\bar{y}^a$ is derived. For analytic convenience, ADR model the accounting signals as arriving in even periods only. Therefore, $\bar{y}^a_t = (y^a_2, \ldots, y^a_t)$. Also a probability measure $\pi^a(y^a, d|\bar{y}^a_t)$ is derived, which has the same interpretation as $\pi$, except that only signals produced by accounting are used to condition liquidating dividend expectations. Accounting value $A_t(\bar{y}^a_t)$ is defined as a valuation measure conditional upon the history of accounting signals.
Therefore, analogous to the market value of the firm $V_t(y_t)$:

$$A_t(\tilde{y}_t) = E_\pi^\alpha(d|\tilde{y}_t^\alpha)(1 + r)^{t-T}. \tag{2}$$

This information setting models the history of accounting signals as a distinguishable valuation determinant amongst multiple sources of information. This is achieved by centering the valuation mechanics on the liquidating dividend, then inducing probability measures about the liquidating dividend conditional upon either the dynamic revelation of all information signals ($\pi$), or the revelation of only accounting signals ($\pi^a$).

It is now possible to define a number of observables within this setting. Assuming the expected rate of return on the period from $\tau$ to $t$ is $r$, that is, $r = E_\pi[(V_t - V_\tau)/V_\tau]$, the unexpected capital gain is:

$$M_{t,\tau}(V_t, \tilde{y}_\tau) \equiv V_t - (1 + r)^{t-\tau}V_\tau(\tilde{y}_\tau). \tag{3}$$

Similarly the unexpected return on the period $t, \tau$ is $R_{t,\tau} \equiv M_{t,\tau}/V_\tau$, with the conventional property that $E_\pi[R_{t,\tau}|\tilde{y}_\tau] = 0.\tag{10}$

ADR define accounting earnings as the change in accounting value, that is:

$$e_t(\tilde{y}_t^a) \equiv A_t(\tilde{y}_t^a) - A_{t-2}(\tilde{y}_{t-2}^a). \tag{4}$$

Following Demski and Sappington [1990] earnings at a given time point $t$ are assumed invertible in their signals $y_t^a$ for any history $\tilde{y}_{t-2}^a$. Therefore, observing earnings always translates to the recovery of the underlying primitive signals $\tilde{y}_t^a$, and hence the ability to distinguish the accounting valuation in (2). The power of this invertibility assumption is in the ability to closely contrast accounting and market observables in terms of accounting analogues to the above market based measures. ADR therefore

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\textsuperscript{10}This last property follows from the dividend expectation process being a martingale. That is,

$$E_\pi[E_\pi(d|\tilde{y}_{t+1})|\tilde{y}_t] = E_\pi(d|\tilde{y}_t)$$
define myopic unexpected earnings $\hat{U}_{t,r}$ as:

$$
\hat{U}_{t,r}(e_t, y^a_r) \equiv e_t - E_{\tau^a}[e_t|y^a_r].
$$

(5)

The important point is that only $\pi^a$ determines myopic earnings expectations.

### 3.2 Information Content in Dynamic Settings

#### 3.2.1 Defining Information Content

Studying information content in this valuation setting implies a study of how information source $\eta$ impacts the valuation process given in (1). That is, an information source has information content if and only if liquidating dividend expectations are altered by $\eta_r$ at some time point $t$ where $\tau \leq t < T$. The intuition is that information content is not confined to the period of signal release. "Information" in this setting may derive from only current period signals, or interactions amongst current period signals, or from their interaction with prior period signals. Assessing information content of an information source requires recognition that the firm's history of all information realizations conditions the interpretation of current signals. The information content of the $\eta_r$ source may be evident at time point $\tau = t$. Alternatively, concatenation with signals from an $\eta_t$ source with $\tau < t < T$, whether it be the same or a different source, may determine the information content of $\eta_r$. The pathological case is where neither signals from the $\eta_r$ source nor the $\eta_t$ source have information content unless concatenation occurs.

Similar properties follow for accounting source $\eta^a_r$ because of the relationship between $\pi$ and $\pi^a$. The difference is that its signals consist of only the $y^a$ series. Definitionally, this offers two notions of information content for accounting source $\eta^a$. Within the accounting domain, $\eta^a$ has information content if liquidating dividend expectations, based upon only $\pi^a$ cause accounting value $A_t(y^a_t)$ to change. Alternatively, within the market domain, $\eta^a$ has information content if dividend expectations are revised based upon $\pi$, therefore causing a change in $V_t(y_t)$. 
The distinction is the allowable interactions because of information dynamics and the existence of multiple information sources. Within the accounting domain, the information content of $\eta_i$ can only derive from the effect of current $y_i$ signals conditional upon the realized accounting history $\bar{y}_{i-1}$. Therefore, the only permissible interactions are between current and prior accounting signals. The market domain utilizes all accounting signals plus multiple other information realizations. Information content derives, not only from the $y$ series, but from its interaction with multiple other information realizations which together conditionally alter $\pi$.

Empirically, the point of inquiry concerns the information content of accounting within the market domain. This translates to a question of how the $y$ series conditionally changes firm value based upon $\pi$ and the valuation process in (1). This requires the recognition that the information content of the accounting source can derive from the $y_i$ signals alone, or the interplay of these current signals with their own history $\bar{y}_{i-1}$, or the interplay with other information sources.

3.2.2 Locating Information Content

Empirical studies on the informativeness of accounting numbers generally confine their search to the period in which the accounting signal is released. But if one allows the interaction of signals with other current and prior period signals, then, as argued above, attaching information content to a given information source in a given time period becomes ambiguous. One is confronted with two approaches to motivate empirical studies of information content: either assume that one can remove the ambiguity in locating information content at the theoretical level by restricting the interpretation of the signals to the period of information release. Alternatively, recognize the nature of the ambiguity in locating the information content of a given periods' signals in a dynamic setting and explicitly factor this into the research design.

The former implies further structural assumptions on the theoretical setting but allows the econometric motivation for contemporaneous regressions of earnings on
returns. To consider this case, ADR allow \( \pi \) to exhibit the Conditional Monotone Likelihood Ratio property (CMLRP). That is, \( \pi \) displays CMLRP if \( \forall t < T, \tilde{y}_{t-1} \in \tilde{Y}_{t-1} \), and \( y_t, y'_t \in Y_t \):

\[
\frac{\pi(y'_t|d', \tilde{y}_{t-1})}{\pi(y_t|d', \tilde{y}_{t-1})} > \frac{\pi(y_t|d', \tilde{y}_{t-1})}{\pi(y'_t|d', \tilde{y}_{t-1})}
\]

for all \( y'_t > y_t \) and \( d' > d \). The interpretation of CMLRP is that irrespective of the realized history \( \tilde{y}_{t-1} \), all possible \( y_t \) signals from \( \eta_t \) have an impact on dividend expectations. Intuitively, observing a ranking of only current period signals with respect to their “newsworthiness”, assumes that \( \pi \) behaves in such a way as to yield a “valuation ranking” consistent with this “newsworthiness” ranking independent of the previous history. Therefore theoretically, all signals have a unique valuation impact in a given time period. This removes concatenative problems with locating information content. That is, it removes problems at the theoretical level of observing signals that are regarded as having “low newsworthiness” having high valuation impact because of concatenation with history.

This study proceeds without the assumption of CMLRP, which may be viewed as a maintained assumption of conventional association studies in locating the valuation information in accounting earnings. By not invoking CMLRP, the study attempts to capture how information continuously conditions liquidating dividend expectations through time. In other words, it models the process of valuation as a continuously interactive process with history through time. Therefore, the focus is on the information content of the accounting source rather than isolating information content of an accounting signal in a given time period.

Empirically, of course, ambiguity in locating information content may not be observed. It may be that valuation behavior is observed consistent with a market using a probability measure \( \pi \) that exhibits CMLRP, therefore removing ambiguity created by historical interactions. But whether this theoretical structure does or does not exist is ultimately an empirical question.
What is required is that the adopted research design be sympathetic towards both scenarios. This is further pursued in Chapter IV.

3.2.3 Information Content and Observables

Observing information content in terms of the accounting and market observables is readily discernable. In the market domain, observing $V_r(y_T) \neq (1 + r)V_{r-1}(y_{r-1})$ implies that $E_\pi[d|y_T] \neq E_\pi[d|y_{r-1}]$. Therefore, $\eta_r$ has information content given the valuation mechanics. ADR express this observation of information content for a given time period $\tau, \tau - 1$ as the non-zero conditional variance of the unexpected return measure $R_{r,\tau-1}$. This follows because the first moment of the unexpected return is zero as mentioned previously. That is, $E_\pi[R_{r,\tau-1}|y_{r-1}] = 0$. But the informational effect of signal $y_T$ is traceable to the conditional variance of $R_{r,\tau-1}$ since $\text{Var}[R_{r,\tau-1}|y_{r-1}] = E_\pi\left( (R_{r,\tau-1}|y_{r-1} - E_\pi[R_{r,\tau-1}|y_{r-1}])^2 \right)$. By construction, $V_r(y_T) - (1 + r)V_{r-1}(y_{r-1})$ nonzero, implies $R_{r,\tau-1}|y_{r-1}$ nonzero, in which case $\text{Var}[R_{r,\tau-1}|y_{r-1}]$ is positive, implying that $\eta_r$ has information content.

But, given the interaction amongst current and prior period signals, the opposite does not necessarily hold. Whereas observing non-zero conditional variance of the unexpected return in the period $\tau, \tau - 1$ suggests information content because of some new signal and/or an interaction, a zero value does not imply no information content. An extreme complementarity case implies that $y_\tau$ without $y_t$ (where $\tau < t < T$) has no information content, and therefore $\text{Var}[R_{r,\tau-1}|y_{r-1}] = 0$. But upon receipt of $y_t$, information content becomes apparent through concatenation with the $y_{t-1}$ history, and therefore $\text{Var}[R_{t,t-1}|y_{t-1}] > 0$. This draws the analysis back to the problem of locating information content. Observance of $\text{Var}[R_{t,t-1}|y_{t-1}] > 0$ may result from the $y_t$ signal independent of the history $y_{t-1}$, alternatively information content may derive from the interplay with the history. Once again, unambiguous interpretation of $\text{Var}[R_{t,t-1}|y_{t-1}]$ at the theoretical level to locate information content of time point $t$ signals requires the special structure of CMLRP. A similar structure exists
for accounting observables. Given invertibility, information source $\eta^*_r$ has information content within the accounting domain if $\text{Var}[\hat{U}_{r,T-2}|\tilde{y}_{r-2}] > 0$.

3.2.4 Empirically Locating Information Content

Empirically, $\pi$ is not observed. The main observable within the market domain is the firm's time series of security prices as realizations from $\pi$ and the valuation mechanics in (1). But, the above theoretical notions generalize to the empirical setting. Specifically, this study views the time series of firm returns as sequential drawings from a distribution whose moments are conditional upon the sequential release of signals about future dividends. For example, assuming that the first two moments of the return distribution are conditioned by informative signals, as might happen when assuming returns are conditionally normal, then at some time point $t - 1$, prior to the release of an informative signal at $t$, the mean and variance of the return distribution depend upon all signal releases to time point $t - 1$. In other words, the history of informative signals $\tilde{y}_{t-1}$ conditions the two moments of the return distribution at $t - 1$. The informational effect of the signal at $t$, is observable in its effect upon these conditional moments. Therefore, a valuation setting consistent with the dynamic nature of $\pi$ suggests that the firm's return distribution can be characterized by the moment effects of the dynamic revelation of all informative signals. As a result, conditional variation in these two moments is interpreted as equivalent to observing the informational effect of the release of all informative signals and as the outcome of a stochastic process driven by $\pi$.

3.3 The Distinguishing Properties of the Accounting Source

To date, the analysis has been primarily concerned with the concept and measurement of information content in a dynamic environment. The accounting source has largely been treated in abstract terms by merely recognizing its potential as a distinguishable provider of valuation relevant information.
The analysis now probes deeper into the institutional setting of the accounting domain which determines the $y^a$ signals and therefore the dynamics of $\pi^a$.

### 3.3.1 Accounting Structure

The financial accounting system plays the major role in the formal reporting of an entities operations. Two characteristics distinguish it from less formal information sources. First, the firm’s time line of operations is broken into discrete units of (generally) twelve months upon which the financial report is prepared. Secondly, financial accounting exhibits many structural rules for reporting the firm events that occur during these twelve month units. Some might be thought of as general in nature. Example are rules that restrict the domain of accounting to the reporting of realized transactions, as well as those rules that derive from the need to report about discrete time units. Examples of the latter are the familiar rules relating to the correct periodic matching of revenue and expense which are seen as embodied in methods of revenue recognition and expense accruals. These rules are an inherent part of the structure of all financial accounting reports irrespective of firm’s economic context and limit both what and how the accounting source disseminates information.

Other rules are more specific in nature. Examples are those that relate to specific industry contexts (for example, oil and gas), or for firm specific transaction types such as gains and losses on foreign currency translations. But the existence of both this general and specific structure forces accounting to proceed as an information source independent of other sources of information. It therefore follows as a natural consequence of the structure of accounting in a setting with multiple information sources to contrast $\pi^a$ and $\pi$. But inherent in such a contrast is a measure of the extent to which the structural rules in accounting (and hence the $y^a$ signals) are able to capture firm value based on $\pi$. Therefore, studying the information content of accounting is more than the isolation of an abstract information source.
It is a study of the extent to which conventional accounting institutions (that is, GAAP) play a role in valuation.

3.4 The Contextual Nature of Accounting Information

A contrast between $\pi$ and $\pi^a$ implies variation in the relationship between unexpected capital gain $M_{t,\pi}$ and myopic unexpected earnings $\hat{U}_{t,\pi}$, and therefore variation in the relative role of accounting structure in the market domain.

3.4.1 Monopolistic Accounting

If accounting is a monopolistic supplier of information for valuation, then no contrast between $\pi$ and $\pi^a$ is experienced. Valuation proceeds in accordance with (1) based upon only the $y^a$ signals. An equivalent relationship must also exist in terms of observables since with $\pi \equiv \pi^a$, $M_{t,\pi-2}(\bar{y}_{t-2}^a) \equiv \hat{U}_{t,\pi-2}(\bar{y}_{t-2}^a)$. All valuation relevant information is conveyed by the the sequence of accounting signals for all firms. This therefore precludes the derivation of information content from other information sources, or from the interaction of accounting signals with other information signals. Accounting structure determines all the valuation relevant signals $y^a$. Therefore, assuming returns conditionally normal suggests that observing conditional variation in the mean and variance of returns unambiguously attaches to the information content of the accounting earnings sequence. In other words, the mean and variance of returns at any given time point are conditional upon the history of accounting earnings.

With the identity of accounting and market observables, information content must be invariant in economic context. $\pi^a$ as a manifestation of accounting structure, unambiguously determines liquidating dividend expectations conditional upon the history $\bar{y}^a$. So it is impossible for anything other than the structural rules of the accounting system to affect firm value. Therefore, there can be no concept of variation of information content under different economic contexts.\(^{11}\)

\(^{11}\)The location of information content is still problematic, since nothing precludes the interaction of current accounting signals with the historical accounting signals. But this is a characteristic of the
3.4.2 Non-monopolistic Accounting

More generally, both the accounting source and other information sources condition \( \pi \). This draws the analysis back to exploring the consequences for valuation studies of the contrast between \( \pi \) and \( \pi^a \). ADR characterize the relationship between accounting and market observables under this scenario as:

\[
M_{t,t-2} = \hat{U}_{t,t-2} + [\epsilon_{t,t-1} + \epsilon_{t-1,t-2} - \epsilon^a_{t,t-2}](1 + r)^{t-T}
\]

where

\[
\begin{align*}
\epsilon_{t,t-1} & \equiv E_\pi(d|\hat{y}_t) - E_\pi(d|\hat{y}_{t-1}) \\
\epsilon_{t-1,t-2} & \equiv E_\pi(d|\hat{y}_{t-1}) - E_\pi(d|\hat{y}_{t-2}) \\
\epsilon^a_{t,t-2} & \equiv E_{\pi^a}(d|\hat{y}^a_{t}) - E_{\pi^a}(d|\hat{y}^a_{t-2})
\end{align*}
\]

The relationship is now dependent upon the bracketed noise terms. Intuitively, these noise terms model expectation changes in the liquidating dividend on the period \( t, t-2 \) because of differences between the full information setting and the accounting domain. But, as ADR note, it is in no sense noise due to random measurement error in \( M_{t,t-2} \) which might be characterized with expectation of zero. Whereas \( E_\pi[\epsilon_{t,t-1} + \epsilon_{t-1,t-2}][\hat{y}_{t-2}] = 0 \), the differences between the accounting and market domains because of accounting structure, suggest that \( E_\pi[\epsilon^a_{t,t-2}][\hat{y}_{t-2}] \neq 0 \). Therefore, in considering the valuation relationship between unexpected earnings and unexpected capital gain within the market domain, a **systematic** bias is created by the bracketed noise terms. But the source of the bias is clear. Because of other information sources and the measurement rules embodied in accounting structure, the observance of unexpected earnings no longer translates to the revision of dividend expectations.

Probing the structure of these noise terms also suggests that the relationship, and therefore the relative size of the noise, term is potentially context specific depending upon how the measurement rules of accounting convey valuation relevant signals relative to other information sources. The above analysis suggests that the relative information dynamics and is definitionally separate from the concept of information content. Under this monopolistic accounting scenario, it is impossible for accounting structure to do a "better job" in determining informative signals under one economic context versus another.
size of the noise term depends upon both the quantity of other information for a
given firm history, since $y_{t-2} \subset y_{t-2}$, and the interaction between accounting and
other information sources for a given history since $E_\pi[\epsilon_{t,t-1} + \epsilon_{t-1,t-2} - \epsilon_{t,t-2}|y_{t-2}] \neq 0$. The context specificity therefore stems from how accounting structure relates to other information sources.

The implication for the empirical setting, is the loss of the unambiguous attachment between conditional moment variation in returns and the information content in the sequence of accounting earnings as in the monopolistic accounting setting. Conditional variation in the mean and the variance now results from market participants' assessments of the sequence of all informative signals. But the structural relationship given in (4) suggests that, if there is information content in the sequence of accounting earnings, then the conditional moments of returns can be explained by the sequence of accounting earnings. That is, at any time point, the history of accounting earnings conditions the mean and variance of firm returns. However, because of the noise terms, the conditional variation in return moments depends upon more than the history of accounting earnings. Other information, and its interplay with accounting information also enters into the conditioning process.

3.5 Generalizing Extant Valuation Studies

The valuation impact (or information content) of accounting earnings is conventionally modeled as the ability of its unexpected portion to associate with unexpected measure of firm returns. In light of the above discussion, three observations are made in generalizing this approach to a dynamic setting. These are that,

1. Potentially all conditional moments of the return distribution are affected by an informative signal.

2. If accounting was a monopolistic supplier of informative signals, then conditional variation in the moments of the distribution of firm returns must derive from the sequential release of accounting signals. That is, in terms of ADR's
analysis, the accounting and market domains are equivalent. Therefore, associating variation in the conditional moments of the distribution of the firm’s returns with the sequential release of firm earnings makes sense in terms of assessing the information content of the accounting source, but,

3. Given the noise terms in (4), this association is thought of in a relative sense. That is, because of the structural conventions of accounting and the existence of other information, the objective is to determine the relative variation in return moments associated with the sequential release of accounting earnings.

These three items are viewed as a relaxation of assumptions of the conventional approach to association studies. In combination, items one and two say that the informational effect of accounting earnings affects more than the location of the firm return—all other shape characteristics of the firm’s return distribution are conditional upon the sequential release of informative (accounting) signals. Further, given item 3, economic context potentially dictates the relative ability of the accounting sequence to characterize conditional variation in the shape and location of returns.

### 3.6 Empirical Hypotheses

Financial ratio analysis traditionally emphasizes contextual interpretation of accounting numbers. In particular, accountants emphasize comparability of ratios within the same industry, based upon arguments that stress commonality of production and investment characteristics, and consequently a commonality in the ability of accounting based metrics to reflect these characteristics within an industry. In a non-monopolistic accounting setting, this suggests cross-sectional variation in the relative ability of accounting numbers to capture production/investment attributes. Given the discussion in this chapter, observing this differing relative ability of accounting to capture these attributes is consistent with a scenario in which the effect of accounting structure and other information varies in cross-section.
The study proposes two empirical hypotheses. Consistent with the dynamics of the valuation setting:

**Hypothesis 1**: Both the firm's history of accounting earnings and its history of past returns condition the shape and location of the current period return distribution.

Consistent with the relative valuation role of accounting earnings under different economic contexts:

**Hypothesis 2**: Industry contexts delineate contextual variation in the information content of the accounting source.

### 3.7 Summary

This chapter articulated four major conceptual propositions.

1. The information content of an information source in a dynamic environment derives from the valuation impact of its signals relative to other informative signals.

2. Observing information content in any given period depends upon the history of prior informative signals.

3. Information content is observed as conditional variation in return moments.

4. Given 1 and 2, the relative information content of accounting signals as the output of one information source depends upon the structural rules and conventions of accounting.

Chapter IV uses these four propositions to derive empirical models for testing Hypotheses 1 and 2.

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12How these hypotheses are formally tested is treated in subsections 5.4.2 and 5.4.3.
CHAPTER IV
Econometric Models

This chapter develops the econometric models to test Hypotheses 1 and 2. The analysis proceeds under the simple notion that at any time point \( t \), the return of firm \( i \) on the period \( t, t-1 \) can be characterized as comprising some expected component given history, and a stochastic unexpected component with mean zero. The central theme of this study, is that not only does information history potentially determine what is expected (that is, the location of returns), but that the shape characteristics of the unexpected return distribution at \( t-1 \) stem from the dynamic conditioning of return moments given new information and its evaluation in light of prior history.

The analysis proceeds in two stages. First, the assumption is made that the conditional effect of new information is upon only the mean and variance of returns. That is, returns are assumed to be conditionally normal. This allows the modeling of returns using the ARCH setting of Engle [1982], and the consequent derivation of the methods of empirical analysis. This informational assumption is then relaxed allowing for the conditional effect of new information to be upon all shape and location characteristics of the return distribution. This involves considering the analysis within the semiparametric framework of Gallant and Tauchen [1989].

4.1 The ARCH model

The ARCH model lends a convenient interpretation of the discussion in Chapter III. Let \( \bar{r}_{it-1} \equiv (r_{it-1}, r_{it-2}, \ldots r_{it-L})' \), denote the history of past returns for a finite period \( L \). Returns are modeled using a conventional autoregressive process, with the
unexpected return captured by the error term. Therefore,

\[ r_{it} = b + B\bar{r}_{it-1} + z'_{it}, \tag{8} \]

where the expected portion of the observed return \( r_{it} \) is modeled as a linear parameterization of its prior values. \( B \) is an \( L \times 1 \) vector of coefficients, with all elements less than one, with the stochastic component of the process \( z'_{it} \), measuring the unexpected return component.

Modeling the effect of the information in the \( \bar{y}_t \) series suggests the imposition of statistical properties on \( z'_{it} \) consistent with the theoretical statistical properties exhibited by \( R_{t,T} \) in Chapter III in revealing information content. Specifically, \( E(z'_{it}) = 0 \), but the variance of \( z'_{it} \) depends upon the sequence of information signals \( \bar{y}_{t-1} \). An ARCH model can accommodate this structure by assuming unexpected returns to be serially uncorrelated (that is, \( \text{Cov}(z'_{it}, z'_{t-1}) = 0 \)), but allowing the variance of the unexpected return to be conditional upon the sequence of prior signals \( \bar{y}_{t-1} \).

The problem is that researchers are unable, (or it is too costly) to identify all of the signals. Firm value realizations from \( \pi \), given the valuation mechanics in Chapter III, reveal only their (temporally) aggregated effect. But the history of unexpected returns captures the informational effect of the signal history. This is because information content is only evident in the event of an unanticipated firm value change. Therefore, the prior history of unexpected returns captures past informative signals to \( t - 1 \) and as such, is used as the conditioning metric for current period unexpected returns. Hence the history of unexpected returns to \( t - 1 \) determines the variance of returns at \( t - 1 \). In the ARCH setting, this is assumed to be a linear function of \( z^2_{it-m} \), where \( 1 \leq m \leq L \).\(^{13}\) Thus, the conditional variance of the unexpected return, is modeled as:

\[ \text{Var}_{t-1}(z'_{it}) = h^*_t = \omega_i + \sum_{m=1}^{L-1} \gamma_{im} z^2_{it-m} \tag{9} \]

\(^{13}\)Chapter III discussed the relationship between unanticipated firm value changes, the unexpected return and the conditional variance of the unexpected return. A nonzero unexpected return \( R_{t,T-1|\bar{y}_{T-1}} \) implies a positive conditional variance since \( \text{Var}[R_{t,T-1|\bar{y}_{T-1}}] \equiv E( R_{t,T-1|\bar{y}_{T-1}} ) \).
where \( \omega_i > 0 \) and \( \gamma_{tm} > 0 \). Intuitively, this is an empirical model in which the second moment of the unexpected return distribution is dependent upon the history of prior unexpected returns. The effect of the information content in the \( y_t \) signals on the return process, is conditional upon the prior signal history \( \tilde{y}_{t-1} \). Thus, the effect of the \( y_t \) signals is to cause an unanticipated firm value change \( z_{it}^2 \). This implies that in modeling the statistical properties of the return process, both its mean and variance at \( t - 1 \) are conditional upon the effect of past signals \( \tilde{y}_{t-1} \). New information at \( t \), in the form of the \( y_t \) signals causes a reassessment of both these moments conditional upon the prior history of unanticipated firm value changes at \( t - 1 \). Hence, consistent with the theoretical setting of Chapter III, information is modeled as driving the conditional moments of returns.

4.1.1 Monopolistic Accounting

With accounting as a monopoly supplier of information \( M_{r,r-2} \equiv \hat{U}_{r,r-2} \). Scaling by \( V_{r-2} \) results in \( R_{r,r-2} \equiv \hat{U}_{r,r-2}/V_{r-2} \), or that the unexpected return is equivalent to the myopic unexpected earnings yield (henceforth, earnings yield). Earnings are assumed fully revealing in their signals. That is, it is assumed that observing reported accounting earnings is equivalent to the observation of the accounting signals previously modeled as \( \tilde{y}^a \). If earnings announcements are made annually, and no other information is available other than the prior history of accounting earnings, the unanticipated firm value change \( M_{r,r-2} \) can only occur annually when the earnings announcement takes place, and the information content (if any) is revealed.

To draw this out further, an empirical model similar to (8) can be proposed. That is, let \( x_{it} \) denote an observation of the earnings yield for firm \( i \). Further, let \( \bar{x}_{it-1} \equiv (x_{it-1}, x_{it-2} \ldots x_{it-L})' \). Then analogous to (8):

\[
x_{it} = c + C\bar{x}_{it-1} + u_{it},
\]

where \( C \) is an \( L \times 1 \) vector of coefficients with all elements less than one, and \( u_{it} \) is the unexpected earnings yield. Moreover, given this monopolistic accounting setting,
$z'_t \equiv u_{it}$ and $c + C\tilde{x}_{it-1} \equiv b + B\tilde{r}_{it-1}$. Unexpected returns are unexpected earnings yields. Therefore, there is an unambiguous attachment between the causal signals in $y_t^a$ (measured by the unexpected earnings yield), and the observed effect in the unexpected returns, which, using (5), implies that,

$$r_{it} = c + C\tilde{x}_{it-1} + u_{it}.$$  \hspace{1cm} (11)

The conditional variance of $u_{it}$ can be modeled as:

$$\text{Var}_{t-1}(u_{it}) = h_{it}^a = \nu_i + \sum_{m=1}^{L-1} \lambda^a_{im}u_{it-m}.$$ \hspace{1cm} (12)

But given this scenario, $h_{it}^r \equiv h_{it}^a$. The effect of information upon the conditional variance of the unexpected earnings yield is identical to the effect upon the conditional variance observed in unexpected returns. Therefore, when accounting is the monopolistic source of information, there are two equivalent formulations for the conditional variance of unexpected returns on the period $t, t-1$: either $h_{it}^r$ or $h_{it}^a$. Similarly, expected returns are equivalently conditional upon either $c + C\tilde{x}_{it-1}$ or $b + B\tilde{r}_{it-1}$.

It now becomes notationally convenient, and for later explanation of the semi-parametric approach, to consider the formulations in (9) and (12) as polynomials in their respective lagged values of $r_i$ and $x_i$. Repetitive substitution of (8) into (9) yields:

$$h_{it}^r = \omega_i + \sum_{m=1}^{L-1} \gamma_{im}(r_{it-m} - b - Br_{it-m-1})^2$$

$$= \text{poly}(\tilde{r}_{it-1}, \xi)$$

where the $\xi$ parameters derive from the expansions in $\omega, b, B$ and $\gamma$, and "poly" denotes a polynomial, with in this case, no term of higher order than two. Similarly, from (11) and (12), $h_{it}^a = \text{poly}(\tilde{x}_{it-1}, \psi)$ where, as before, the $\psi$ parameters derive from expansions in $\nu, c, C$, and $\lambda$. Let $\theta_r \equiv \{b, B, \xi\}$ and $\theta_a \equiv \{c, C, \psi\}$ with $\theta_r, \theta_a \in \Theta$. Assume further that a time series of $T$ observations is available. In this setting of monopolistic accounting, there are two equivalent characterizations of the conditional
distribution of returns. One is returns conditioned on past returns \((\bar{r}_{it-1})\) and \(\theta_a\), and one conditioned on past earnings yields \((\bar{x}_{it-1})\) and \(\theta_r\). Therefore, each of the \(T\) observations can be viewed as a drawing from a distribution of returns whose mean and variance depend upon either the past values of returns and \(\theta_r\), or equivalently the past values of earnings yields and \(\theta_a\). Therefore, the likelihood functions \(L(r_{it}|\bar{r}_{it-1}, \theta_r)\) and \(L(r_{it}|\bar{x}_{it-1}, \theta_a)\) are equivalent.

Now, the basic estimation procedure which is expanded by the semiparametric approach is introduced. This is done at this point to merely indicate that the proposed parametric models of the return process are estimable from the data and to motivate the analysis for contrasting the two return models. Estimation of the true values of \(\theta_a\) and \(\theta_r\) can be achieved using maximum likelihood estimation. If \(z'_{it}\) is assumed to be conditionally normal, that is, \(z_{it} \sim N(0, h_{it})\), then Engle and Bollerslev [1986] proposed the log-likelihood function:

\[
\log L(r_{it}|A, \theta) = -\frac{T}{2} \log(2\pi) - \frac{1}{2} \sum_{t=1}^{T} \left[ \log h_{it} + \frac{(r_{it} - b - BA)^2}{h_{it}} \right],
\]

where, given the above discussion, \(\theta = \theta_r \equiv \theta_a\) and \(h_{it} = h^a_{it} \equiv h^r_{it}\) and \(A = \bar{x}_{it-1} \equiv \bar{r}_{it-1} \).

### 4.1.2 Non-Monopolistic Accounting

Recall from Chapter III, that the relationship in (7) implied the loss of an unambiguous relationship between accounting and market observables in the non-monopolistic accounting setting. Accordingly, it can be deduced that \(h^r_{it} \neq h^a_{it}\), \(b + B\bar{r}_{it-1} \neq c + C\bar{x}_{it-1}\), and therefore that \(\theta_r \neq \theta_a\). Therefore, in the non-monopolistic accounting setting, only accounting signals are used to model information content via \(L(r_{it}|\bar{r}_{it-1}, \theta_a)\). As a consequence, relative to \(L(r_{it}|\bar{r}_{it-1}, \theta_r)\), it is informationally restricted. But it is assumed analogous to (7) that a mapping exists between the parameter spaces \(\theta_r\) and \(\theta_a\), or that there exists a vector valued function \(g^a\), such that \(\theta_r = g^a(\theta_a)\). Intuitively, this formalizes in a more general setting, the common notion in association studies that there exists some mapping between the valuation
signals in accounting earnings and the firms (unexpected) return. The difference is in explicitly recognizing that because of accounting structure and other information, a systematic difference exists requiring the imposition of the restrictions imposed by \( g^a \).

These restrictions are interpreted as the implicit information loss because of accounting structure and other information. This is because of the identity of the two return likelihoods under the monopolistic accounting setting. A measure of this "information loss" between each of the characterizations \( L(r_{it}|\bar{x}_{it-1}, \theta_a) \) and \( L(r_{it}|\bar{r}_{it-1}, \theta_r) \) under differing industry contexts serves as a basis for testing Hypothesis 2. That is, the statistical distance between the subspaces \( \theta_r \) and \( \theta_a \) is interpreted as existing because accounting earnings is potentially informationally restricted relative to all information. Therefore, measuring the distance between these likelihoods becomes the empirical analogue to the noise terms portrayed in equation (7) of Chapter III. In other words, measuring the contrast between \( \pi \) and \( \pi^a \) under different industry contexts translates to this distance measure.

### 4.1.3 Akaike's Information Criterion

To formalize this contrast between these likelihoods, the loss function proposed by Akaike [1973] is adopted. Applied to \( L(r_{it}|\bar{x}_{it-1}, \theta_a) \) this is:

\[
W(\theta^o_r, \hat{\theta}_a) = -\frac{2}{T} \int \left[ \log \left( \frac{L(r_{it}|\bar{x}_{it-1}, \hat{\theta}_a)}{L(r_{it}|\bar{x}_{it-1}, \theta^o_r)} \right) \right] \frac{L(r_{it}|\bar{r}_{it-1}, \theta^o_r)}{L(r_{it}|\bar{r}_{it-1}, \theta^o_r)} \, dr_it,
\]

where \( L(r_{it}|\bar{x}_{it-1}, \hat{\theta}_a) \) is the likelihood maximum using (13), and is treated as a constant in the integration, and \( \theta^o_r \) is the true value of \( \theta_r \). Akaike proposed this loss function for discriminating amongst competing regression models. The loss function is two times the Kullback-Leibler information (see Kullback [1959]) for discriminating in favor of \( L(r_{it}|\bar{x}_{it-1}, \theta^o_r) \) over \( L(r_{it}|\bar{x}_{it-1}, \theta_a) \). It can be shown that \( W(\theta^o_r, \hat{\theta}_a) \geq W(\theta^o_r, \theta^o_r) = 0 \) or that the greater the distance between \( \theta^o_r \) and the subspace \( \theta_a \), the greater the value of \( W \). \( \theta^o_r \) is not known because it is the true value.
However, Akaike devised an unbiased metric to predict $W$ known as the Akaike Information Criterion (AIC). Given the hypothesis that $\theta_r = g^a(\theta_a)$, AIC$^a$ is computed as:

$$AIC^a = -\frac{2}{T} \log L(r_{it}|\bar{x}_{it-1}, \hat{\theta}_a) + \frac{2p^a}{T},$$

(15)

where $p^a$ is the number of parameters in $\hat{\theta}_a$. Amemiya [1980] provides a review of why the AIC is an unbiased predictor of $W(\theta^o_r, \hat{\theta}_a)$. AIC offers a measure of distance between $L(r_{it}|\bar{x}_{it-1}, \hat{\theta}_a)$, and $L(r_{it}|\bar{r}_{it-1}, \theta^o_r)$. In other words, it predicts how well the characterization of the joint density of $r_{it}$, formed from a sample of $T$ observations and conditional on the history of accounting signals $[L(r_{it}|\bar{x}_{it-1}, \hat{\theta}_a)]$, is to the true (but unknown) characterization based on the effect of all signals $[L(r_{it}|\bar{r}_{it-1}, \theta^o_r)]$.

Akaike's purpose behind the criterion was to rank competing explanatory models of a given dependent variable relative to the true model. The smaller the AIC, the smaller the predicted value of $W$, hence the closer the parameterization to the true model. In this study the AIC, as an unbiased estimate of the Kullback-Leibler information, is used to measure the distance between the two likelihood functions $L(r_{it}|\bar{x}_{it-1}, \hat{\theta}_a)$ and $L(r_{it}|\bar{r}_{it-1}, \hat{\theta}_r)$, since clearly the AIC for the latter characterization can be computed using the maximum likelihood estimate of $\theta_r$ (AIC$^r$). A priori, it is expected that the AIC for $L(r_{it}|\bar{x}_{it-1}, \hat{\theta}_a)$ is larger than the AIC for $L(r_{it}|\bar{r}_{it-1}, \hat{\theta}_r)$, because of the effect of accounting structure and other information. Accordingly, it is expected that $W(\theta^2_r, \hat{\theta}_a) > W(\theta^2_r, \hat{\theta}_r)$.

Note that, consistent with the intuition in Chapter III, under the monopolistic accounting setting, $L(r_{it}|\bar{x}_{it-1}, \hat{\theta}_a) \equiv L(r_{it}|\bar{r}_{it-1}, \hat{\theta}_r)$, which implies that $W(\theta^2_r, \hat{\theta}_a) - W(\theta^2_r, \hat{\theta}_r) = 0$, for all industries. Therefore, the analysis is consistent with not observing a dependence of relative information content upon industry context in the monopolistic accounting setting. In other words, measuring the distance between the likelihood functions is consistent with the economic scenario of information and valuation discussed in Chapter III.

---

$^{14}$To this end, the intuition behind the AIC is similar to adjusted $R^2$ in conventional linear regressions.
4.2 The Semiparametric Approach

The analysis to date has proceeded under the assumption that the dynamics of information content can be adequately captured with the simple ARCH models portrayed in (8) and (9), and (11) and (12). This approach is now generalized in two ways. First, the normality assumptions with respect to the distribution of unexpected returns is relaxed so as to allow information content to be a manifestation of any conditional shape variation in the unexpected component of each of the return models. Second, no assumptions about the functional relationship between conditional shape variation and the history of prior signals are made. In the ARCH models, the conditional variance was assumed to be a linear function of past squared unexpected returns \( h_{it} \) or earnings yields \( h_{it}^{a} \). This assumption is now relaxed to capture the effect of information on all conditional moments, not just the mean and variance as has been done to date.

Specifically, the approach used in Gallant and Tauchen [1989] (G&T) is adopted. Usually, when undertaking maximum likelihood estimation, it is assumed that each data observation is drawn from some underlying distribution which is (usually) characterized by its mean and variance. In section 4.1, the distribution of \( z_{it} \) was characterized as conditionally normal with mean zero and conditional variance \( h_{it} \). Therefore, taking the log of the likelihood function for \( T \) observations gave the expression in (13).

The intuition behind the semiparametric approach of G&T is that a priori the data is assumed conditionally normal. However, should the data further reveal that some departures from conditional normality exist, then the the distribution of \( z_{it} \) is adapted for conditional shape and location departures. This adapted distribution then serves as the basis of the likelihood function, with parameter estimation proceeding within the usual maximum likelihood framework.

It is assumed that all \( r_{it} \) and \( x_{it} \) observations are from a stationary time series, and that the conditional distribution of \( r_{it} \) depends upon only a finite number of past observations \( L \) as previously. The analysis commences with the return generation
process modeled in (8):  
\[ z_{it}' = r_{it} - b - B \tilde{r}_{it-1}. \]  
(16)

Converting \( z_{it}' \) to a standardized residual using its true standard deviation \( \sigma_r \), defines \( z_{it} \) as:  
\[ z_{it} = \left( \frac{r_{it} - b - B \tilde{r}_{it-1}}{\sigma_r} \right). \]  
(17)

Rather than assuming the conditional density of \( r_{it|\tilde{r}_{it-1}} \) is normal, G&T derive the true conditional density, \( h(r_{it|\tilde{r}_{it-1}}) \), from some parent density \( f \), via a change of variables. That is:  
\[ h(r_{it|\tilde{r}_{it-1}}) = f \left[ \frac{(r_{it} - b - B \tilde{r}_{it-1})}{\sigma_r} \right] \sigma_r^{-1}. \]  
(18)

The focus of the analysis is the determination of a good approximant to \( f(z_{it}) \). This is accomplished by recognizing that a Hermite polynomial times the standard normal density approximates \( f(z_{it}) \), where the degree of the polynomial is dictated by the data. Using the terminology that \( \phi(z_{it}) \) denotes the standard normal density of the standardized residual \( z_{it} \), the intuition is to adjust for departures from normality using a polynomial in \( z_{it} \) times the standard normal density. That is:  
\[ f(z_{it}) = \text{poly} \{a_r, z_{it}\}^{K_z} \phi(z_{it}), \]  
(19)

where \( K_z \) is the degree of the polynomial part of the density, and the \( a_r \) constants are the coefficients of the polynomial terms. To be a density, it must always be positive and integrate to one. G&T achieve this by squaring the polynomial part and dividing by the integral over the real line. Therefore, dropping the firm \( i \) subscripts:  
\[ f_{K_z}(z_t) = \left[ \sum_{\alpha=0}^{K_z} a_{r\alpha} z_t^\alpha \right]^2 \phi(z_t) / \int \left[ \sum_{\alpha=0}^{K_z} a_{r\alpha} w^\alpha \right]^2 \phi(w) \, dw. \]  
(20)

where \( K_z \) is the degree of the polynomial in \( z_t \), and the density \( f \) depends upon \( K_z \). If the leading "a" coefficient is normalized to one, then for \( K_z = 0 \), \( f(z_t) \) is the standard normal density. Therefore, the effect of \( K_z > 0 \) is to adapt the standard normal density for shape departures from normality exhibited by the data.
But this form of the density does not accommodate shape variation conditional upon history. That is, all moments other than the mean are assumed constant. Whether there is variation in the conditional shape of the density is the basis of Hypothesis 1. To remedy this, G&T allow the data to dictate once again how this dependency on the past is determined. Any form of conditional heterogeneity in the data can be accommodated in the approximation to the true density. This is done by making the $a_r$ coefficients in (19) and (20), polynomials in the past history. That is, each $a_{r_0}$ coefficient in (20) is replaced by a polynomial in the past history. Note that this is consistent with the original ARCH specification, in that $h_t = \text{poly}(\bar{r}_{t-1}, \xi)$ for modeling conditional heterogeneity in the variance only. Therefore, modeling conditional heterogeneity based upon $L$ past returns, $\bar{r}_{t-1}$ results in each $a_{r_0}$ coefficient being given by:

$$a_{r_0}(\bar{r}_{t-1}) = \sum_{|\beta|=0}^{K_r} a_{r_0 \beta} r^{\beta}$$

(21)

where

$$\beta = (\beta_1, \beta_2, \ldots, \beta_L)$$

(22)

$$|\beta| = \sum_{i=1}^{L} \beta_i$$

(23)

$$r^{\beta} = \prod_{i=1}^{L} (r_{t-i})^{\beta_i}$$

(24)

This terminology appears tedious, but its implementation is discussed in Chapter V. Consequently, the density for a standardized residual conditional on $\bar{r}_{t-1}$, $f_K(z_t|\bar{r}_{t-1})$ is given by:

$$\left[ \sum_{\alpha=0}^{K_z} a_\alpha(\bar{r}_{t-1}) z_t^{\alpha} \right]^2 \phi(z_t) \int \left[ \sum_{\alpha=0}^{K_z} a_\alpha(\bar{r}_{t-1}) w^{\alpha} \right]^2 \phi(w) dw,$$

(25)

where $K \equiv (K_z, K_r)$.

Recall from equation (18), that it is assumed the true density of $r_t|\bar{r}_{t-1}$, $h(r_t|\bar{r}_{t-1})$ can be obtained from the parent density $f$, via a change of variables. The density $h_K(r_t|\bar{r}_{t-1})$, depends upon the parameters $b, B, \sigma_t^2$ and all $a_r$ coefficients. Therefore,
\( \theta_r \equiv \{ a_{r, \alpha, \beta}, \sigma_r^2, b, B \} \). Manipulating (25) and using (18), produces the parameterized version of the conditional density \( h_K(r_t | \bar{r}_{t-1}, \theta_r) \):

\[
\left[ \sum_{\alpha=0}^{K} a_{r, \alpha} (\bar{r}_{t-1}) (z_t)^\alpha \right]^2 N(r_t | b + B\bar{r}_{t-1}, \sigma_r^2) \left/ \int \left[ \sum_{\alpha=0}^{K} a_{r, \alpha}(\bar{r}_{t-1}) w^\alpha \right]^2 \phi(w) dw, \tag{26} \]

where the terminology, \( N(r_t | b + B\bar{r}_{t-1}, \sigma_r^2) \), is the normal distribution with mean \( b + B\bar{r}_{t-1} \), and variance \( \sigma_r^2 \). Given a sample of \( T \) observations within each industry, the likelihood function \( L(r_t | \bar{r}_{t-1}, \theta_r) \), can be formed in the usual way as:

\[
L(r_t | \bar{r}_{t-1}, \theta_r) = \prod_{i=1}^{T} h(r_t | \bar{r}_{t-1}, \theta_r), \tag{27} \]

with maximization of the natural logarithm of this likelihood over the parameter space \( \Theta \) deriving the maximum likelihood estimates of \( \theta_r \).

The same analysis follows for \( L(r_t | \bar{x}_{t-1}, \theta_x) \). Use of (11) implies a standardized residual:

\[
u_t = \left( \frac{r_t - c - C\bar{x}_{t-1}}{\sigma_x} \right), \tag{28} \]

where \( \sigma_x \) is the true standard deviation of the earnings yield. Use of the history of earnings yields \( \bar{x}_{t-1} \) instead of the history of past returns \( \bar{r}_{t-1} \) in the above analysis results in the conditional density \( h_K(r_t | \bar{x}_{t-1}, \theta_x) \) being given by:

\[
\left[ \sum_{\alpha=0}^{K} a_{x, \alpha} (\bar{x}_{t-1}) (u_t)^\alpha \right]^2 N(r_t | c + C\bar{x}_{t-1}, \sigma_x^2) \left/ \int \left[ \sum_{\alpha=0}^{K} a_{x, \alpha}(\bar{x}_{t-1}) w^\alpha \right]^2 \phi(w) dw, \tag{29} \]

where, analogous to equations (21) to (24):

\[
a_{x, \alpha}(\bar{x}_{t-1}) = \sum_{|\beta|=0}^{K_x} a_{x, \alpha \beta} x^\beta \tag{30} \]

with

\[
\beta = (\beta_1, \beta_2, \ldots, \beta_L) \tag{31} \]

\[
|\beta| = \sum_{i=1}^{L} \beta_i \tag{32} \]

\[
x^\beta = \prod_{i=1}^{L} (x_{t-i})^{\beta_i}. \tag{33} \]
Similarly, $K \equiv (K_u, K_x)$ denotes the degree of the required polynomials to control for departures from normality and conditional heterogeneity respectively with $\theta_a \equiv \{a_{x\beta}, \sigma_x^2, c, C\}$. With a sample of $T$ observations within each industry, it follows that:

$$L(r_t | \bar{x}_{t-1}, \theta_x) = \prod_{i=1}^{T} h(r_i | \bar{x}_{t-1}, \theta_a),$$

with maximization of the natural logarithm of this likelihood over the parameter space $\theta_a$, deriving the maximum likelihood estimates of $\theta_a$.

### 4.3 Contrasts with the ARCH Model

The advantage in using the semiparametric methodology over the ARCH model is that any form of conditional heterogeneity in unexpected returns based on either the history of returns or the history of earnings yields can be accommodated. The argument in Chapter III was that conditional variation in the return moments was the outcome of market participants continual assessments of information in light of firm information history. Under the ARCH model, returns were assumed conditionally normal with the consequent informational effects apparent in conditional variation of the mean and variance. This then allowed measurement of the distance between the likelihood functions $L(r_t | \bar{r}_{t-1}, \hat{\theta}_r)$ and $L(r_t | \bar{x}_{t-1}, \hat{\theta}_a)$ using the AIC as an unbiased estimate of the Kullback-Leibler information, and as a statistical measure of the inherent information loss in characterizing returns with earnings yields.

The semiparametric approach has allowed a generalization of this analysis in that the likelihood functions $L(r_t | \bar{r}_{t-1}, \hat{\theta}_r)$ and $L(r_t | \bar{x}_{t-1}, \hat{\theta}_a)$ now accommodate any form of conditional moment variation. Measuring the distance between these likelihoods using the AIC now provides a measure of information loss irrespective of how information causes conditional variation in return moments, or which moments are more susceptible to conditional variation because of information in a given industry context. This follows from not assuming any prior density of returns for a given industry context or explicitly placing a functional form on how the moments that determine
the shape of the density conditionally vary with history. As a result, the semiparametric approach is adopted as the methodology for gathering evidence on Hypotheses 1 and 2.

4.4 Summary

The objective of this chapter was to devise econometric models to capture the contrast between $\pi$ and $\pi^a$ and in so doing, provide a methodology for testing Hypotheses 1 and 2.

The analysis proceeded in two stages. The first adopted an ARCH model in which returns were assumed conditionally normal. This assumption allowed considerable simplification, in that the only conditional moments of returns which vary in the sequence of information through time were assumed to be the mean and variance. This approach resulted in the proposal of two likelihood functions, one in which returns were conditional on the history of returns, the other in which returns were conditional on the history of earnings yields. The argument was that in the monopolistic information setting of Chapter III, these two likelihoods are equivalent. However, in a non-monopolistic setting, the distance between the likelihoods is a statistical measure of the information loss because of accounting structure and other information. To provide this distance measure, Akaike’s Information Criterion as an unbiased estimate of Kullback-Leibler information was proposed.

The analysis was then extended to consider a semiparametric derivation of the contrasting likelihood functions. This allowed the relaxation of the conditional normality assumption on returns as well as assumptions on how conditional moments vary with information. Therefore, measuring the distance between two semiparametric likelihoods allows a statistical measure of information loss irrespective of the underlying density of returns, or how the conditional moments vary with information.
Chapter V considers how these semiparametric return models were implemented within the chosen industries for testing Hypotheses 1 and 2, and the methods of analysis implemented using AIC.
CHAPTER V
Methods

This chapter documents the methods used in the study for hypothesis testing. Four procedural areas are considered. First, the sample selection criteria within the chosen industries are presented. This also includes a discussion of data sources and computational procedures necessary for the data. Second, the procedures to implement the semiparametric likelihood functions detailed in Chapter IV are discussed. Third, model selection procedures are reviewed. Finally, the methods used for gathering evidence on the hypotheses are considered.

5.1 Industry and Sample Selection Criteria

Under Hypothesis 2, the study considers four industries and attempts to isolate a difference in the relative information content of accounting earnings for valuation on average across time. The argument in Chapter III was that this difference arises from economic contexts created by production and investment circumstances of firms operating within different industries. Because accounting adopts a set of rules and conventions under GAAP that not only break the reporting cycle of economic events into twelve month units, but dictate how economic events should be reported for these time units, the potential exists for the structure of the reporting system to influence market valuation. Also, the availability of financial information outside of the accounting reporting system and how it relates to what is reported by accounting potentially affects the relative valuation impact of the accounting source. This was the contrast between $\pi$ and $\pi^a$ articulated in Chapter III.
As expressed in Chapter II, little research exists on how the structure of the accounting system *per se* associates with firm valuation. Consequently, when choosing industries to analyze under Hypotheses 1 and 2, the approach was to use some loose priors to isolate a potential contrast.

Retailing is typically characterized as operating in twelve month cycles which accords with how accountants break up the time line for earnings measurement purposes. Further, the major revenue earning activity is relatively simple to measure in that it loosely consists of the turnover of assets on a short-term basis. Similarly, although banking is simple in nature consisting essentially of the borrowing and lending of money, earnings are subject to how macroeconomic conditions impact the fortunes of their short and long-term investment portfolios. On the other hand, an industry like mining is typically characterized as having long production cycles with a good deal of uncertainty in what and when revenues and expenses should be recognized within these twelve month time units. Similarly, heavy manufacturing firms generally operate under long-term contracts with considerable uncertainty in revenue and expense measurement. Therefore, the choice of these industries accords with some loose intuition about the nature of accounting measurement within these industries, as well as the conventional "wisdom" mentioned in Chapter III of performing financial statement analysis within industries.

A second issue is that the analysis in Chapters III and IV has taken place considering an individual firm *i* within a given industry. Unfortunately, time series of the length necessary to estimate \( \theta_r \) and \( \theta_a \) are not available. Consequently, cross-sectional pooling of data across time is necessary to meet data requirements. This procedure necessarily carries with it caveats about capturing homogeneity of production and investment characteristics within each chosen industry.

Tables 1 and 2 indicate the chosen industries for study. Firms within these industry groups were selected using 2-digit SIC codes from Standard and Poor's COMPU-STAT II files. All firms are either NYSE or AMEX listed.
Table 1.
Breakdown of the Chosen Industry Samples for Mining and Heavy Manufacture & Machinery by 2-Digit SIC Code.a

<table>
<thead>
<tr>
<th>Industry</th>
<th>2-Digit SIC</th>
<th>Number of Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>MINING:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Metal, Gold &amp; Silver Ores</td>
<td>10</td>
<td>13</td>
</tr>
<tr>
<td>Coal &amp; Lignite Mining</td>
<td>12</td>
<td>1</td>
</tr>
<tr>
<td>Crude Petroleum &amp; Natural Gas</td>
<td>13</td>
<td>15</td>
</tr>
<tr>
<td>Petroleum Refining</td>
<td>29</td>
<td>19</td>
</tr>
<tr>
<td>Total Firms</td>
<td></td>
<td>48</td>
</tr>
<tr>
<td>Total Observations</td>
<td></td>
<td>642</td>
</tr>
<tr>
<td>HEAVY MANUFACTURE &amp; MACHINERY:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Steel Manufacture</td>
<td>33</td>
<td>42</td>
</tr>
<tr>
<td>Metal Fabrication</td>
<td>34</td>
<td>25</td>
</tr>
<tr>
<td>Manufacturing &amp; Office Machinery</td>
<td>35</td>
<td>21</td>
</tr>
<tr>
<td>Total Firms</td>
<td></td>
<td>88</td>
</tr>
<tr>
<td>Total Observations</td>
<td></td>
<td>1408</td>
</tr>
</tbody>
</table>

a Appendices A and B provide full sample details.
Table 2.
Breakdown of the Chosen Industry Samples for Retailing and Banking Services by 2-Digit SIC code.a

<table>
<thead>
<tr>
<th>Industry</th>
<th>2-Digit SIC</th>
<th>Number of Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>BANKING SERVICES:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Commercial Banks, Savings Institutions</td>
<td>60</td>
<td>19</td>
</tr>
<tr>
<td>Credit Institutions, Mortgage Bankers</td>
<td>61</td>
<td>10</td>
</tr>
<tr>
<td>Total Firms</td>
<td></td>
<td>29</td>
</tr>
<tr>
<td>Total Observations</td>
<td></td>
<td>464</td>
</tr>
<tr>
<td><strong>RETAILING:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Department, Variety Stores</td>
<td>53</td>
<td>11</td>
</tr>
<tr>
<td>Grocery Stores</td>
<td>54</td>
<td>9</td>
</tr>
<tr>
<td>Clothing Stores</td>
<td>56</td>
<td>4</td>
</tr>
<tr>
<td>Radio, TV, Electrical Stores</td>
<td>57</td>
<td>1</td>
</tr>
<tr>
<td>Eating Places</td>
<td>58</td>
<td>1</td>
</tr>
<tr>
<td>Drug, Jewelry, Hobby Stores</td>
<td>59</td>
<td>7</td>
</tr>
<tr>
<td>Total Firms</td>
<td></td>
<td>33</td>
</tr>
<tr>
<td>Total Observations</td>
<td></td>
<td>528</td>
</tr>
</tbody>
</table>

a Appendices C and D provide full sample details.
5.1.1 Data Collection

It was required that each firm have a sixteen year earning's history for the period 1972-1987 inclusive. Further, it was necessary that a complete monthly return history be available on CRSP for the period 1972-1988, as well as end of month stock prices to compute the required earnings yields. The procedure adopted was to aggregate cross-sectionally each firm time series within each industry, then estimate the parameters for each return model from this cross-sectionally aggregated sample.\textsuperscript{15} Specific data computations for each return model are given as follows.

$L(r_t|\bar{r}_{t-1}, \theta_r)$: Equation (8) in Chapter IV dictates the data requirements given the chosen time period for testing. For firms having a complete return and earnings history, the month of the fiscal year end was identified. Returns were cumulated for nine months prior to the fiscal year end and for the three months after fiscal year end. Further, due to length of the time series available within each firm, the maximum lag length for conditioning on history was set at three years. That is, the maximum size of $\bar{r}_{t-1}$ was $(r_{t-1}, r_{t-2}, r_{t-3})'$. For example, setting time $t$ as the annual return for the 1988 fiscal period resulted in $\bar{r}_{t-1} \equiv (r_{1987}, r_{1986}, r_{1985})'$. Consequently, there is a loss of three observations within each firm. For lag lengths of less than three years, the same sample size of thirteen observations was preserved within each firm as for a lag length of three years.

$L(r_t|\bar{z}_{t-1}, \theta_a)$: Equation (11) in Chapter IV dictates the data requirements. Earnings yields were computed for the fiscal years 1972-87 inclusive. This was done by pulling the primary earnings per share (before discontinued operations and extraordinary

\textsuperscript{15}As a result of this procedure of cross-sectional aggregation, some cross-sectional dependence within each industry sample is to be expected. Therefore, one would expect that a priori, some inflation of the standard error of the parameter estimates may take place because the data is no longer independent. The parameter estimates are not used to draw inferences concerning the hypotheses in this study. This is done with AIC, and, as Amemiya [1980] notes, the AIC does not require that the data be independent. Accordingly, this procedure of cross-sectional pooling of the data across time is unlikely to have any major influence upon the inferences made in the study.
items) from COMPUSTAT and scaling it by the stock price recorded on CRSP at the month-end just prior to the beginning of the return cumulation. For example, a two year earnings history $\bar{x}_{t-1}$ (that is, $L = 2$), where return period $t$ is for the fiscal year 1988 and the firm's fiscal year end is December, resulted in the earnings per share being pulled for the years 1986 and 1987 and each being scaled by the stock price at the end of March 1986 and March 1987 respectively. This is done to correspond with the deflator implicit in a return history for the same time period. As with the return history, a loss of three observations occurs when the lag length is set at three years. Further, for lag lengths of less than three years, the same sample size was preserved as with a lag length of three years.

The final issue with respect to scaling of the data. G&T note the necessity to scale the data for implementation of the semiparametric likelihood functions discussed in Chapter IV. Accordingly, all computations are based upon standardized data within each firm. That is, the mean and standard deviation are estimated from the sixteen observations within in each firm and used to standardize all raw data observations within each firm.

5.2 Derivation and Implementation of the Likelihood Functions

This subsection considers implementation of the general form of the likelihood functions depicted in equations (21),(26) and (29),(30) for $L(r_t|\bar{r}_{t-1}, \theta_r)$ and $L(r_t|\bar{x}_{t-1}, \theta_a)$ respectively. Recall from Chapter IV that the structure of a given likelihood function depends upon three items:

1. The lag length $L$, of the conditioning history, since this determines the length of the vector $\bar{r}_{t-1}$ for $L(r_t|\bar{r}_{t-1}, \theta_r)$ and the consequent number of $B$ parameters. Similarly, $L$ determines the length of the vector $\bar{x}_{t-1}$ for $L(r_t|\bar{x}_{t-1}, \theta_a)$ and the consequent number of $C$ parameters.
2. The degree of the polynomial to accommodate departures from normality in the data. For \( L(r_t|\bar{r}_{t-1}, \theta_r) \), this was \( K_z \) and for \( L(r_t|\bar{x}_{t-1}, \theta_a) \) this was \( K_u \).

3. The degree of the polynomial controlling conditional dependency of the shape of the return density on history. As discussed in Chapter IV the degree of this polynomial is \( K_r \) for \( L(r_t|\bar{r}_{t-1}, \theta_r) \), and for \( L(r_t|\bar{x}_{t-1}, \theta_a) \) it is \( K_x \).

The terminology \( \text{SP}_r(L, K_z, K_r) \) and \( \text{SP}_x(L, K_u, K_x) \) is adopted for respective parameterizations of the likelihoods \( L(r_t|\bar{r}_{t-1}, \theta_r) \) and \( L(r_t|\bar{x}_{t-1}, \theta_a) \). As was discussed in Chapter IV, the objective behind the semiparametric approach is to let the data determine the structure of the conditional moments of returns for each likelihood characterization. In this way the method builds from the data the optimum model of how shape and location vary with information on average across time. However, this "building" an optimum model from the data requires that for each of \( L(r_t|\bar{r}_{t-1}, \theta_r) \) and \( L(r_t|\bar{x}_{t-1}, \theta_a) \) the optimum values of \( L, K_z, K_r \) and \( L, K_u, K_x \) be located. Just how these optimum values are found is considered in subsection 5.3. But the outcome is that many different parameterizations of the likelihood functions must be tested based upon varying both \( L, K_z, K_r \) and \( L, K_u, K_x \).

5.2.1 Examples of Likelihood Functions

To demonstrate the procedures for deriving these parameterizations, three examples are considered. These are an \( \text{SP}_r(2, 0, 0) \), an \( \text{SP}_r(2, 2, 0) \) and an \( \text{SP}_r(2, 2, 1) \). This choice was made to show the impact of each of the variables \( L, K_z \) and \( K_r \) have on the parameterization of the likelihood \( L(r_t|\bar{r}_{t-1}, \theta_r) \). Exactly the same procedures are adopted for \( L(r_t|\bar{x}_{t-1}, \theta_a) \).

\( \text{SP}_r(2, 0, 0) \): This is the simplest form of parameterization in that the data is assumed normal (\( K_z = 0 \)) and only the location of returns depends upon two lags of past returns (\( L = 2 \) and \( K_r = 0 \)). There is no conditional shape variation because of history and information has no effect on moments higher than the mean of returns.
The conditional density of returns is normal with conditional mean \( b - B\bar{r}_{t-1} \) and variance \( \sigma_r^2 \). That is, \( h(r_t|\bar{r}_{t-1}, \theta_r) \) is given by:

\[
\frac{1}{(2\pi\sigma_r^2)^{1/2}} \exp \left[ -\frac{1}{2} \left( \frac{r_t - (b - B\bar{r}_{t-1})}{\sigma_r} \right)^2 \right],
\]

with \( \bar{r}_{t-1} \equiv (r_{t-1}, r_{t-2})' \).

**SP_r(2,2,0):** In this example, a second order polynomial adapts the normal distribution for shape departures from normality \( (K_z = 2) \), but the shape does not vary with the history of returns \( (\bar{r}_{t-1}) \) since \( K_r = 0 \). In other words, the shape of the return distribution does not vary with the sequential release of information through time, unlike the location of returns, which, at any annual time point, is dependent on the two prior period returns \( r_{t-1} \) and \( r_{t-2} \). Deriving the conditional density \( h(r_t|\bar{r}_{t-1}, \theta_r) \), requires the use of equations (21) and (26) in Chapter IV. Since \( K_r = 0 \), the polynomial portion of the numerator in (26) is:

\[
a_0 + a_1 z_t + a_2 z_t^2,
\]

where, from (17), \( z_t = \frac{r_t - b - B\bar{r}_{t-1}}{\sigma_r} \). Similarly the polynomial portion of the denominator of (26) is:

\[
a_0 + a_1 w_t + a_2 w_t^2,
\]

Applying (26), the conditional density \( h(r_t|\bar{r}_{t-1}, \theta_r) \) is therefore:

\[
\int \frac{[a_0 + a_1 z_t + a_2 z_t^2]^2}{(2\pi\sigma_r^2)^{1/2}} \exp \left[ -\frac{1}{2} \left( \frac{r_t - (b - B\bar{r}_{t-1})}{\sigma_r} \right)^2 \right] \phi(w) \, dw.
\]

**SP_r(2,2,1):** This example differs from the previous **SP_r(2,2,0) example** in so far as the shape of the return density at any given annual time point now depends upon two lags of past returns since \( K_r = 1 \). Therefore, specifications in which all three of the variables \( L \), \( K_z \) and \( K_r \) are positive, are parameterizations of a return density which, under the theoretical setting of Chapter III, are argued to exist because of the
effect of information on all return moments. As outlined in Chapter IV, the procedure

to accommodate conditional shape variation is to make each "a" coefficients in (38)
a polynomial in the return history. In the example, this needs to be a polynomial of
degree one (since \( K_r = 1 \)) in two lags (since \( L = 2 \)). This implementation is done using

expressions (21) to (24) in Chapter IV. First, note from (22) that \( \beta = (\beta_1, \beta_2) \). Second,

these \( \beta \)'s are used to determine the powers of the polynomial terms. Therefore, the

\( \beta \)'s can only be positive integers by the definition of a polynomial. Thus, if \( |\beta| = 0 \)
this implies, using (23), that \( \beta_1 \) and \( \beta_2 \) can only take the values \((0,0)\) because the

sum of their absolute values must be zero. Similarly, for \( |\beta| = 1 \), implies the only two

possibilities are \((1,0)\) and \((0,1)\) for the values of \( \beta_1 \) and \( \beta_2 \). Since \( K_r = 1 \), then \( |\beta| \)
terminates at 1 via expression (23). Therefore, each \( a \) coefficient in (38) becomes

\[
a_0(\bar{r}_{t-1}) = a_{0;00} + a_{0;10}r_{t-1} + a_{0;01}r_{t-2} \quad (39)
\]

\[
a_1(\bar{r}_{t-1})z_t = \{a_{1;00} + a_{1;10}r_{t-1} + a_{1;01}r_{t-2}\}z_t \quad (40)
\]

\[
a_2(\bar{r}_{t-1})z_t^2 = \{a_{2;00} + a_{2;10}r_{t-1} + a_{2;01}r_{t-2}\}z_t^2, \quad (41)
\]

where the two digits after the semicolon indicate the respective powers \( r_{t-1} \) and \( r_{t-2} \)
after applying (24). For example, the term \( "a_{0;10}r_{t-1}" \) derives as one of the three terms
resulting from making the \( a_0 \) coefficient in (37) a polynomial in the two lags. That
is, it is the second term in the summation of (21), and is formed when \( \alpha = 0, |\beta| = 1 \)
and \( r^\theta = r_{t-1}^\theta r_{t-2}^\theta \).

Therefore, the conditional density \( h(r_t|\bar{r}_{t-1}, \theta_r) \) derives from replacing the poly­
nomial part of the numerator in (38) with the sum of (39),(40) and (41). Similarly,

replacing \( z \) with \( w \) in (37) determines the polynomial in the denominator integral. As

a result, parameterizations of \( h(r_t|\bar{r}_{t-1}, \theta_r) \) in which all three of the variables \( L, K_z \)
and \( K_r \) are positive are considerably more complex than those in which \( K_r = 0 \).

5.2.2 Implementation Issues

There are three implementation issues for deriving the log-likelihood function from

the conditional density \( h(r_t|\bar{r}_{t-1}, \theta_r) \). These are:
1. the appropriate form of the log-likelihood given the method of optimization used to derive the parameter estimates of \( \theta_r \),

2. the normalization rule given each parameterization of \( h(r_t|\bar{r}_{t-1}, \theta_r) \) must be comparable, and

3. evaluation of the denominator integral in parameterizations of \( h(r_t|\bar{r}_{t-1}, \theta_r) \) when \( K_z > 0 \).

These are now considered in turn.

**The Log-likelihood Function:** For a sample of \( T \) observations in a given industry, the relationship between the likelihood function and the conditional density of returns was given in equation (27) of Chapter IV as:

\[
L(r_t|\bar{r}_{t-1}, \theta_r) = \prod_{i=1}^{T} h_K(r_t|\bar{r}_{t-1}, \theta_r),
\]

where \( K \equiv (K_z, K_r) \). Rather than performing the maximization of the natural log of (42) to obtain the maximum likelihood estimates of \( \theta_r \), an equivalent approach minimizes the negative value of the log-likelihood. The reason for this approach centers on the particular optimization routine adopted in the study, in that it minimizes a nonlinear objective function subject to constraints.\(^{16}\) As a result, the log-likelihood minimized over the parameter space \( \Theta \) is:

\[
\log L(r_t|\bar{r}_{t-1}, \theta_r) = -\frac{1}{T} \sum_{i=1}^{T} \log h_K(r_t|\bar{r}_{t-1}, \theta_r).
\]  

**Normalization and the Number of Parameters:** As mentioned in Chapter IV, applying the normalization rule of setting the leading "a" to one ensures that all parameterizations of \( h_K(r_t|\bar{r}_{t-1}, \theta_r) \) are comparable independent of the values of \( L, K_z \) and \( K_r \). The notation \( p_\theta \) is used to denote the length of a vector containing the number of unconstrained parameters for any given log-likelihood function. Therefore, to complete the examples of this subsection, Table 3 indicates how \( p_\theta \) is determined.

\(^{16}\)The actual optimization procedures are further described in subsection 5.2.3.
Table 3.
Determining the Length of $p_\theta$ for the Likelihood Function Examples.

<table>
<thead>
<tr>
<th>Example</th>
<th>Number of a Coefficients</th>
<th>Other Coefficients $\sigma^2, b, B$</th>
<th>Normalization</th>
<th>$p_\theta = (1) + (2) + (3)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SP_r(2,0,0)</td>
<td>0</td>
<td>4</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>SP_r(2,2,0)</td>
<td>3</td>
<td>4</td>
<td>-1</td>
<td>6</td>
</tr>
<tr>
<td>SP_r(2,2,1)</td>
<td>9</td>
<td>4</td>
<td>-1</td>
<td>12</td>
</tr>
</tbody>
</table>

The Denominator Integral: For all parameterizations of $h_K(r_t|t_{t-1}, \theta_r)$ for which $K_z > 0$, the denominator contains an integral over the real line to ensure that the density integrates to one. Implementing the log-likelihood function requires that this integral be evaluated. For the SP_r(2,2,0) this integral was:

$$\int [a_0 + a_1 w_t + a_2 w_t^2]^2 \phi(w) \, dw.$$  \hspace{1cm} (44)

Squaring the polynomial portion results in:

$$\int a_0^2 + 2a_0a_1 w_t + 2a_0a_2 w_t^2 + a_1^2 w_t^2 + 2a_1a_2 w_t^3 + a_2^2 w_t^4 \phi(w) \, dw.$$  \hspace{1cm} (45)

Moving the integral inside this summation results in the sum of terms involving the product of constants and integrals of $w$ times the standard normal density $\phi(w)$. These integrals are the moments of the standard normal density. That is, $\int \phi(w) \, dw = 1$, $\int w^2 \phi(w) \, dw = 1$, $\int w^4 \phi(w) \, dw = 3$, $\int w^6 \phi(w) \, dw = 15$ and $\int w^8 \phi(w) \, dw = 105$. But all $\int w^i \phi(w) \, dw = 0$ for $i$ odd. Therefore, for any given set of a coefficients, the
integral evaluates to a constant. For parameterizations in which $K_r > 0$, considerably more terms are involved. For example, squaring the polynomial in the denominator of the $SP_r(2, 2, 1)$ example involves 45 unique terms rather than the 6 unique terms evaluated in (45).

5.2.3 Optimization Technique

Optimization of the log-likelihood functions was performed using subroutine E04UCF in the fortran subroutine library NAGlib. E04UCF is designed to solve nonlinear programming problems that involve the minimization of a smooth nonlinear function subject to a set of constraints on the variables. The only constraint in this application is the normalization of the leading $a$ coefficient when $K_z > 0$. All problems for which $K_z$ and $K_r = 0$ are unconstrained. The optimization problem for $K_z > 0$ is therefore:

$$\min_{\theta_r \in \Theta} \log L(r_t|\bar{r}_{t-1}, \theta_r)$$
$$st: \quad a_1 = 1.$$  

E04UCF use a sequential quadratic programming algorithm to locate downhill directions from a set of user-supplied starting values for $\hat{\theta}_r$. This iterative search proceeds until for some $\hat{\theta}_r$, a first order Kuhn-Tucker point is located within the optimality tolerance chosen by the user. For this study, the optimality tolerance was set at $10^{-5}$ which, according to the specifications of the algorithm, yields an accuracy at the optimum value of the objective function to four places of decimals. Because of the heavy computational load in locating the global optimum for some of the heavily parameterized likelihoods, all optimizations were carried out using the CRAY-YMP8 Supercomputer at The Ohio State University.

5.3 Model Selection Procedures

Recall from Chapter IV that the testing method for Hypotheses 1 and 2 involves characterizing and contrasting the likelihood functions $L(r_t|\bar{r}_{t-1}, \theta_r)$ and $L(r_t|\bar{\varepsilon}_{t-1}, \theta_a)$. 
within each chosen industry. To do this requires selection of the parameterization under each of these likelihoods that best fits the data. The purpose of this subsection is to detail the procedures for selection of these optimal parameterizations based upon the sample data within each industry.

5.3.1 Deriving and Analyzing the Likelihood Surface

As the previous subsection detailed, there are multiple parameterizations of the likelihoods \( L(r_t|\bar{r}_{t-1}, \theta_r) \) and \( L(r_t|\bar{x}_{t-1}, \theta_a) \) depending on the values of \( L, K_z \) and \( K_r \) for the first likelihood, and \( L, K_u \) and \( K_x \) for the second. Optimization of each log-likelihood for a given set of values of these variables yields a particular global minimum. For example, the log-likelihoods for each of \( SP_r(2,0,0) \), \( SP_r(2,2,0) \) and \( SP_r(2,2,1) \) demonstrated in the previous subsection will each yield a minimum value for \( \log L(r_t|\bar{r}_{t-1}, \theta_r) \). Further, as Table 3 demonstrated, each is a more heavily parameterized version of the conditional density \( h \), in which case at the optimum point under each parameterization, \( SP_r(2,0,0) > SP_r(2,2,0) > SP_r(2,2,1) \).

Two points arise from these observations. First, consider \( L(r_t|\bar{r}_{t-1}, \theta_r) \): as \( L, K_z \), and \( K_r \) are varied independently along three dimensions, there exists a global optimum for the multiple parameterizations of the log-likelihood function \( \log L(r_t|\bar{r}_{t-1}, \hat{\theta}_r) \) given the sample data. Therefore, the problem of the best fit to the data becomes one of searching this surface of global optima to find that parameterization that best characterizes the data. In other words, use of the term "best" denotes the search along each of the dimensions \( L, K_z \) and \( K_r \) and so in this sense is unconstrained.

Second, to perform this search procedure, some rule is necessary to locate the best parameterization. The definition of "best" adopted in the study is when no statistically significant improvement (p-value = 0.05) occurs by moving from the current

\[ -\frac{1}{T} \log L(r_t|\bar{r}_{t-1}, \hat{\theta}_r) \]

for each of these parameterizations will satisfy these inequalities.

\[ ^{17} \text{That is, the value of } -\frac{1}{T} \log L(r_t|\bar{r}_{t-1}, \hat{\theta}_r) \text{ for each of these parameterizations will satisfy these inequalities.} \]

\[ ^{18} \text{As noted previously, data limitations have restricted } a \ priori \text{ the length of } L \text{ to three years. As a practical matter, Chapter VI indicates that the best fits to the data tended to be shorter than this lag length.} \]
global optimum point on the likelihood surface to a lower point by increasing the number of parameters in the likelihood function. This is done using the asymptotic \( \chi^2 \) distribution of the conventional likelihood ratio test.

An example is presented to clarify these procedures. Table 4 illustrates the likelihood surface for \( L(r_t|F_{t-1}, \hat{\theta}_r) \) based on the sample of 624 observations that comprise the mining industry sample.

The first five columns of the table characterize the surface. These show global optima for the different parameterizations of \( L(r_t|F_{t-1}, \theta) \) that derive from \( L, K_z \) and \( K_r \). As the next subsection will exploit, each line tells a "story" with respect to the conditional distribution of firm returns on average across the sample period. The objective is to locate the best parameterization and so the model that best characterizes this conditional distribution of firm returns.

As mentioned above, this search procedure is performed using the likelihood ratio test. The likelihood ratio is:

\[
LR = 2[\log L(\psi^u) - \log L(\psi^r)],
\]

where \( \log L(\psi^u) \) is the unrestricted log-likelihood minimum and \( \log L(\psi^r) \) the restricted log-likelihood minimum determined by setting \( k \) parameters to zero. The statistic is asymptotically \( \chi^2 \) with \( k \) degrees of freedom.\(^{19}\) The search process involves locating the model for which no significant reduction in the likelihood minimum takes place by going to a more heavily parameterized model. Table 5 illustrates a portion of Table 4. Contrasting an \( SP_r(1,2,0) \) with an \( SP_r(2,2,0) \) using the formula in (47) yields a \( \chi^2 \) statistic of \((2)(624)(-1.3198-(-1.3573))=46.80\) with (6-5) degrees of freedom, which has a \( p \)-value of < 0.01. Therefore, as the boldfaced \( p \)-value in the "L" column indicates, an \( SP_r(2,2,0) \) is a significantly better fit than an \( SP_r(1,2,0) \). As Table 6 indicates, moving to an \( SP_r(3,2,0) \) specification is insignificant, as indicated by the boldfaced \( p \)-value of 0.50 in the "L" column for the \( SP_r(2,2,0) \).\(^{20}\)

\(^{19}\)See Amemiya [1985], for a detailed proof of the likelihood ratio test.

\(^{20}\)Following G&T, the minimum specification that accommodates departures from normality is \( K_z = 2 \). Therefore, an \( SP_r(1,0,0) \) is followed by an \( SP_r(1,2,0) \).
Table 4.
Example of the Likelihood Surface, $L(r_t | \bar{r}_{t-1}, \hat{\theta}_r)$
for the Sample of Mining Firms.
Sample Size: 624 observations

| $L$ | $K_z$ | $K_r$ | $p_0$ | $-\frac{1}{T} \log L(r_t | \bar{r}_{t-1}, \hat{\theta}_r)$ | $p$-value |
|-----|-------|-------|------|---------------------------------|-----------|
| 0   | 0     | 0     | 2    | 1.392408                        | .01       |
| 0   | 2     | 0     | 4    | 1.364629                         | .01       |
| 0   | 3     | 0     | 5    | 1.364281                         |           |
| 1   | 0     | 0     | 3    | 1.386604                         | .01       |
| 1   | 2     | 0     | 5    | 1.357315                         | .01       |
| 1   | 2     | 1     | 8    | 1.353468                         | .01       |
| 1   | 3     | 1     | 10   | 1.348772                         |           |
| 2   | 0     | 0     | 4    | 1.360606                         | .50       |
| 2   | 2     | 0     | 6    | 1.319852                         | .50       |
| 2   | 2     | 1     | 12   | 1.310263                         | .15       |
| 2   | 2     | 2     | 21   | 1.301770                         | .30       |
| 2   | 3     | 0     | 7    | 1.318171                         |           |
| 3   | 0     | 0     | 5    | 1.360182                         |           |
| 3   | 2     | 0     | 7    | 1.319751                         |           |
Table 5.
Illustrating the Choice of Lag Length
for the Likelihood Surface, $L(r_t|\bar{r}_{t-1}, \hat{\theta}_r)$
for the Sample of Mining Firms—Step 1.

| $L$ | $K_z$ | $K_r$ | $p_0$ | $-\frac{1}{2} \log L(r_t|\bar{r}_{t-1}, \hat{\theta}_r)$ | $L$ | $K_z$ | $K_r$ |
|-----|-------|-------|-------|-----------------------------------|-----|-------|-------|
| 0   | 0     | 0     | 2     | 1.392408                          | .50 | 0     | .01   |
| 0   | 2     | 0     | 4     | 1.364629                          | .01 | .01   | .50   |
| 0   | 3     | 0     | 5     | 1.364281                          |     |       |       |
| 1   | 0     | 0     | 3     | 1.386604                          |     |       |       |
| 1   | 2     | 0     | 5     | 1.357315                          | .01 | .01   | .20   |
| 1   | 2     | 1     | 8     | 1.353468                          | .01 | .07   |       |
| 1   | 3     | 1     | 10    | 1.348772                          |     |       |       |
| 2   | 0     | 0     | 4     | 1.360606                          | .50 | 0     | .01   |
| 2   | 2     | 0     | 6     | 1.319852                          | .5  | .15   | .06   |
Table 6. Illustrating the Choice of Lag Length for the Likelihood Surface, $L(r_t|\bar{r}_{t-1}, \hat{\theta}_r)$ for the Sample of Mining Firms—Step 2.

| $L$ | $K_z$ | $K_r$ | $p_0$ | $-\frac{1}{2} \log L(r_t|\bar{r}_{t-1}, \hat{\theta}_r)$ | $p$-value |
|-----|------|------|------|------------------------------------------------|-----------|
| 2   | 0    | 0    | 4    | 1.360606                                   | .50       |
| 2   | 2    | 0    | 6    | 1.315118                                   | .50       |
| 2   | 2    | 1    | 12   | 1.310263                                   | .15       |
| 2   | 2    | 2    | 21   | 1.301770                                   | .06       |
| 2   | 3    | 0    | 7    | 1.318171                                   | .30       |
| 3   | 0    | 0    | 5    | 1.360182                                   |           |
| 3   | 2    | 0    | 7    | 1.319751                                   |           |
Table 7. Illustrating the Choice of $K_z$ for the Likelihood Surface, $L(r_t | \hat{\theta}_{t-1}, \hat{\theta}_r)$ for the Sample of Mining Firms.

| $L$ | $K_z$ | $K_r$ | $p$ | $-\frac{1}{T} \log L(r_t | \hat{\theta}_{t-1}, \hat{\theta}_r)$ | p-value |
|-----|-------|-------|-----|---------------------------------|---------|
| 2   | 2     | 0     | 4   | 1.360606                        | .50     |
| 2   | 2     | 0     | 6   | 1.315118                        | .15     |
| 2   | 2     | 1     | 12  | 1.310263                        | .06     |
| 2   | 2     | 2     | 21  | 1.301770                        | .30     |
| 2   | 3     | 0     | 7   | 1.318171                        |         |
| 3   | 0     | 0     | 5   | 1.360182                        |         |
| 3   | 2     | 0     | 7   | 1.319751                        |         |

Determining the appropriate value of $K_z$ follows the same procedure as with $L$. As Table 7 illustrates, no significant improvement takes place in the fit to the data by moving to a third order polynomial to control for departures from normality over that offered by a second order polynomial as indicated by the boldfaced $p$-value in the $K_z$ column of Table 7. Finally, determining whether the best fit to the data suggests a shape dependence conditional on two lags of returns is done by contrasting the $SP_r(2,2,0)$ model with an $SP_r(2,2,1)$. As the boldfaced $p$-value indicates in the $K_r$ column of Table 8, at a 5% significance level, no improvement to the fit takes place. Therefore, the conclusion from this analysis is that based on the sample data, the conditional distribution of firm returns is best characterized by an $SP_r(2,2,0)$ model. That is, on average across the sample period, the location of returns was best characterized as conditionally dependent on a two year return history. However, the shape of the distribution was not conditionally dependent on history. In other
words, although the distribution of unexpected returns is non-normal (given $K_z > 0$), no conditional variation in higher moments was observed. Given that this study interprets conditional moment variation as the outcome of a process by which investors reassess liquidating dividend expectations conditional upon history, this observation suggests that for the given time period, only the location of returns is conditional on information.

5.4 Gathering Evidence on the Hypotheses

5.4.1 The Naive Model

To conclude this chapter, the link is established between the methods of analysis in the previous subsections and the hypotheses.

Recall from Chapters III and IV that information caused conditional variation in return moments as market participants continuously evaluated new signals about the liquidating dividend in light of the history of prior signals. Therefore, observing conditional variation in return moments is interpreted in this study as the observed
outcome of this conditioning process. In terms of the methods outlined in the previous subsections, conditional variation in return moments is only observed if either $L > 0$ (location) or both $L > 0$ and $K_r > 0$ (both shape and location) for $L(r_t|\tilde{r}_{t-1}, \theta_r)$, for the best fit to the data.

The corollary to this dynamic information setting is one in which market participants never alter liquidating dividend expectations based on the conditioning effect of new information. In this case, the best fit to the data would be a model in which $L = 0$ and $K_r = 0$. That is, the location and shape of the return distribution across the sample time period never alters and, as a result, the best fit to the data is a model in which all elements of uncertainty (the return moments) are (conditionally) constant across time. In other words, investors never revise expectations about the liquidating dividend across the sample time period. Consequently, within the theory of Chapter II, there is no information content in any signal released by any potential source of information. The location of returns is a constant and all higher moments are constant.

Examples of models that display no variation in return moments include an $SP_r(0,0,0)$, an $SP_r(0,2,0)$ and an $SP_r(0,3,0)$. The difference between these examples is the $K_r$ term. But this term has nothing to do with conditional variation in the distribution of returns—it merely adjusts for non-normality in the data. In other words, an $SP_r(0,3,0)$ model says that the shape and location of returns are constant over the sample period, but required a third order polynomial to adjust for non-normality in the data. There was no informational effect observed in the conditional moments of returns. These remained constant across the sample time period. Therefore, the model that best fits the data in which both $L$ and $K_r$ are constrained to zero is referred to as the naive model.

The importance of the naive model lies in providing a convenient anchor point to assess relative information content. To see this, note that the naive model is a constrained version of the likelihood $L(r_t|\tilde{r}_{t-1}, \hat{\theta}_r)$ where $\tilde{r}_{t-1} \equiv \{0\}$, and that the
best model is the unconstrained characterization of the likelihood \( L(r_t|\hat{\theta}_r) \). If conditional moment variation is a necessary component of the best fit to the data, then there is a statistical information loss in terms of Kullback-Liebler information if returns are characterized with the naive model, as distinct from the best fit to the data. An estimate of this information loss is possible by computing the difference between the AIC's for each of the naive and best likelihood parameterizations. The fact that this difference exists indicates that non-constant conditional moments are important in characterizing the data—a phenomena that this study attributes to the continuous processing of all informative signals. Further, the size of this distance between the naive likelihood and the best likelihood provides a measure of the marginal effect of characterizing the return process with the informational outcome observed in its conditional moments as distinct from one in which the moments are unconditionally constant. Therefore, this distance is adopted as a statistical measure of the total valuation information observable because of the conditional variation in all return moments.

A measure of the relative valuation information in the accounting earnings as a valuation source is available by the same argument. That is, the question arises as to how much of this total valuation information can be captured by conditioning returns on earnings yields using \( L(r_t|\tilde{\theta}_a) \). This can be done by determining the best fit to the data of returns conditioned on earnings yields, computing its AIC, then determining the proportion of the total valuation information captured by adopting the best model of returns conditioned on earnings yields. Therefore, the closeness of the likelihoods \( L(r_t|\tilde{\theta}_a) \) and \( L(r_t|\hat{\theta}_r) \) relative to the naive model forms the basis of the assessment of the relative valuation information provided by earnings yields.
5.4.2 Gathering Evidence on Hypothesis 1

Hypothesis 1 is concerned with whether the data suggests a return process in which, on average across the sample time period, the shape and location of the return distribution is conditional on the prior history of returns or earnings yields. Should the naive model within each industry, always prove to be the best fit to the data, then this is evidence to suggest that neither the shape nor location of returns is conditional on history. Partial refutation would arise should the best fit to the data be models in which \( L > 0 \) but \( K_r \) or \( K_x \) are zero. In this case, the location but not the shape derives from a conditional return process.

5.4.3 Gathering Evidence on Hypothesis 2

Hypothesis 2 is concerned with observing cross-industry differences in the relative valuation information in accounting earnings on average across the sample time period.

Assume that Hypothesis 1 is at least partially accepted. That is, at least \( L > 0 \) for the best fit to the data for returns conditioned on past returns \( (L(r_t|\bar{r}_{t-1}, \hat{\theta}_r)) \) and return conditioned on past earnings yields \( (L(r_t|\bar{x}_{t-1}, \hat{\theta}_a)) \). This ensures that there is at least some information content over and above the naive model. Therefore, as described above, evidence consistent with Hypothesis 2 involves first measuring the total amount of Kullback-Leibler information gained when discriminating in favor of the best model of \( L(r_t|\bar{r}_{t-1}, \hat{\theta}_r) \) over the naive model, then determining what proportion of this total gained by discriminating in favor of \( L(r_t|\bar{x}_{t-1}, \hat{\theta}_a) \) over the naive model. This proportion serves as the indicator of the relative information content in characterizing returns with conditional moments based on the history of earnings yields over and above characterizing the conditional moments of returns with the history of returns. Consequently, it is consistent with the method of econometric analysis developed in Chapter IV.
This chapter documents the results of applying the methods of Chapter V to the sample data within the four industry classifications. Further, it provides an analysis of the evidence gathered in support of each of Hypotheses 1 and 2.

The chapter proceeds by consecutively presenting an analysis of the likelihood surfaces for each of \( L(r_t|\bar{r}_{t-1}, \hat{\theta}_r) \) and \( L(r_t|\bar{e}_{t-1}, \hat{\theta}_a) \) within each of the industry samples disclosed in Tables 1 and 2. From this analysis, the naive model, the model of best fit for returns conditioned on the history of returns and the model of best fit for returns conditioned on the history of earnings yields are determined. These latter two models will be referred to as the best return model and the best earnings model respectively.

Evidence in support of Hypothesis 1 is then presented within each industry. This is followed by an assessment of the relative valuation information within each industry using the method of section 5.4. Once all industries have been analysed, a number of cross-industry comparisons are made. This involves a comparison of the chosen models across industries and presentation of the evidence in support of Hypothesis 2. A discussion of the empirical findings of the study then follows. The chapter closes with a consideration of limitations of the analysis and possible future extensions.
6.1 Analysis within Industries

6.1.1 Mining

Tables 9 and 10 present the likelihood surfaces for the Mining industry. The models chosen as best fits to the data are shown in boldface.

Likelihood Surface Analysis: The likelihood surface for choice of the return model has already been considered as the example in Chapter V. This resulted in the choice of an $SP_r(2,2,0)$ as the best fit to the return data. Constraining $L$ and $K_r$ to zero results in the choice of an $SP_r(0,2,0)$ as the naive model.

Exploring the likelihood surface in Table 10 for the earnings model results in the choice of an $SP_x(1,2,0)$, or that the best fit to the data when explaining the shape and location of the distribution of annual returns with earnings yields is a model in which next year's mean return is conditional on the current earnings yield, but that all higher moments were constant across the sample time period.

Hypothesis 1: Given that neither the best return nor the best earnings model is the naive model, then the data is consistent with the notion that, on average, the distribution of the one year ahead annual return is conditional on the current information set incorporated in the current and prior year's return as in the return model, or the current period's earnings yield as in the earnings model. But only partial support for Hypothesis 1 is exhibited within this industry. That is, no conditional shape dependence is observed. All moments higher than the mean are constant, or in other words, the moments of the distribution of unexpected returns for each of the return models are constant for the time period sampled.

The Relative Valuation Information in Accounting Earnings: Table 11 provides an analysis of the relative valuation information in the accounting earnings sequence using the method outlined in section 5.4 of Chapter V.
Table 9.
Mining:
Likelihood Surface for
Returns Conditioned on Past Returns.
Sample Size: 624 observations

| $L$ | $K_z$ | $K_r$ | $p_\theta$ | $-\frac{1}{T} \log L(r_t|\hat{\theta}_{t-1}, \hat{\theta}_r)$ | $L$ | $K_z$ | $K_r$ | AIC$^r$ |
|-----|-------|-------|------------|---------------------------------|-----|-------|-------|---------|
| 0   | 0     | 0     | 2          | 1.392408                        | .01 | .01   |       | 2.7912  |
| 0   | 2     | 0     | 4          | 1.364629                        | .01 | .50   |       | 2.7420  |
| 0   | 3     | 0     | 5          | 1.364281                        |     |       |       | 2.7444  |
| 1   | 0     | 0     | 3          | 1.386604                        | .01 | .01   |       | 2.7828  |
| 1   | 2     | 0     | 5          | 1.357315                        | .01 | .05   | .20   | 2.7306  |
| 1   | 2     | 1     | 8          | 1.353468                        | .01 | .07   |       | 2.7324  |
| 1   | 3     | 1     | 10         | 1.348772                        |     |       |       | 2.7294  |
| 2   | 0     | 0     | 4          | 1.360606                        | .50 | .01   |       | 2.7340  |
| 2   | 2     | 0     | 6          | 1.319852                        | .50 | .15   | .06   | 2.6588  |
| 2   | 2     | 1     | 12         | 1.310263                        | .30 |       |       | 2.6589  |
| 2   | 2     | 2     | 21         | 1.301770                        |     |       |       | 2.6707  |
| 2   | 3     | 0     | 7          | 1.318171                        |     |       |       | 2.6586  |
| 3   | 0     | 0     | 5          | 1.360182                        |     |       |       | 2.7362  |
| 3   | 2     | 0     | 7          | 1.319751                        |     |       |       | 2.6618  |
Table 10.
Mining:
Likelihood Surface
for Returns Conditioned on Past Earnings Yields.
Sample Size: 624 observations.

| $L$ | $K_u$ | $K_x$ | $p_\theta$ | $-\frac{1}{2} \log L(r_t | \tilde{r}_{t-1}, \hat{\theta}_u)$ | $p$-value | $L$ | $K_u$ | $K_x$ | AIC$^a$ |
|-----|------|------|------------|---------------------------------|----------|---|-----|-----|-------|
| 0   | 0    | 0    | 2          | 1.392408                        | .50      | .50| .50 | .06 | 2.7912 |
| 1   | 0    | 0    | 3          | 1.391947                        | .50      | .50| .01 | .06 | 2.7934 |
| 1   | 2    | 0    | 5          | 1.361455                        | .50      | .50| .06 | .06 | 2.7388 |
| 2   | 0    | 0    | 4          | 1.391590                        |          |   |     |     | 2.7958 |
| 2   | 2    | 0    | 6          | 1.361240                        |          |   |     |     | 2.7416 |
Table 11.
Mining:
Analysis of the Relative Valuation Information in Accounting Earnings.

<table>
<thead>
<tr>
<th>Model</th>
<th>$p_g$</th>
<th>AIC</th>
<th>Cumulative Decrease in AIC</th>
<th>%-Cumulative Decrease in AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>$SP_r(0,2,0)$</td>
<td>4</td>
<td>2.7420</td>
<td>0.0000</td>
<td>0.0%</td>
</tr>
<tr>
<td>$SP_r(1,2,0)$</td>
<td>5</td>
<td>2.7388</td>
<td>0.0032</td>
<td>3.9%</td>
</tr>
<tr>
<td>$SP_r(2,2,0)$</td>
<td>6</td>
<td>2.6588</td>
<td>0.0832</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

The striking feature of Table 11 is the poor performance of the earnings model relative to the return model. Only 3.9% of the estimated Kullback-Leibler information, over and above the naive model, could be captured using the earnings model. The evidence is consistent with the history of earnings yields being a poor conditioning variable for the location of returns, or that the sequence of earnings releases poorly characterizes the market valuation process. Therefore, based on this analysis of the sample data, the conclusion suggested is that earnings performs relatively badly as a source of valuation information within the mining industry.

A final observation is the length of history required to characterize the conditional mean under each return model. This is deferred until subsection 6.2 when comparisons of this phenomena across industries are made.

6.1.2 Heavy Manufacture & Machinery

Tables 12 and 13 present the likelihood surfaces for Heavy Manufacture & Machinery.
Table 12.
Heavy Manufacture & Machinery:
Likelihood Surface for
Returns Conditioned on Past Returns.
Sample Size: 1144 observations

| $L$ | $K_z$ | $K_r$ | $p_0$ | $-\frac{1}{2} \log L(r_t|\tilde{r}_{t-1}, \hat{\theta}_r)$ | $p$-value | $L$ | $K_z$ | $K_r$ | AIC$^r$ |
|-----|-------|-------|-------|-------------------|----------|-----|-------|-------|--------|
| 0   | 0     | 0     | 2     | 1.348926          | .01      | .01 | 2.7013 |
| 0   | 2     | 0     | 4     | 1.320299          | .01      | .20 | 2.6474 |
| 0   | 3     | 0     | 5     | 1.319500          | .04      | .11 | 2.6227 |
| 1   | 0     | 0     | 3     | 1.337683          | .12      | .01 | 2.6804 |
| 1   | 2     | 0     | 5     | 1.306007          | .04      | .30 | 2.6207 |
| 1   | 2     | 1     | 8     | 1.304461          | .02      | .40 | 2.6227 |
| 1   | 3     | 0     | 6     | 1.304974          |          |     | 2.6203 |
| 1   | 3     | 1     | 10    | 1.303553          |          |     | 2.6245 |
| 2   | 0     | 0     | 4     | 1.336512          | .03      | .01 | 2.6799 |
| 2   | 2     | 0     | 6     | 1.303136          | .05      | .15 | 2.6167 |
| 2   | 2     | 1     | 12    | 1.299381          | .01      | .30 | 2.6196 |
| 2   | 2     | 2     | 21    | 1.294791          |          |     | 2.6261 |
| 3   | 0     | 0     | 5     | 1.334543          |          | .01 | 2.6777 |
| 3   | 2     | 0     | 7     | 1.301469          |          | .04 | 2.6150 |
| 3   | 2     | 1     | 16    | 1.293887          |          | .40 | 2.6156 |
| 3   | 2     | 2     | 34    | 1.289362          |          |     | 2.6380 |
Table 13.
Heavy Manufacture & Machinery:
Likelihood Surface for
Returns Conditioned on Past Earnings Yields.
Sample Size: 1144 observations.

| $L$ | $K_u$ | $K_x$ | $p_0$ | $-\frac{1}{2} \log L(r_t | \hat{\theta}_u)$ | $p$-value | $\frac{L}{K_u}$ | $K_x$ | AIC$^a$ |
|-----|-------|-------|-------|-------------------------------------------|----------|----------------|-------|--------|
| 0   | 0     | 0     | 2     | 1.348926                                 | .15      | 2.7013         |
| 1   | 0     | 0     | 3     | 1.347957                                 | .25      | .01            | 2.7010 |
| 1   | 2     | 0     | 5     | 1.320257                                 | .02      | .20            | .02    | 2.6491 |
| 1   | 2     | 1     | 8     | 1.315411                                 | .01      | .06            | .02    | 2.6447 |
| 1   | 3     | 0     | 6     | 1.319489                                 |          |                | 2.6493 |
| 1   | 3     | 1     | 10    | 1.313147                                 |          |                | 2.6436 |
| 2   | 0     | 0     | 4     | 1.347367                                 | .02      |                 | 2.7016 |
| 2   | 2     | 0     | 6     | 1.317561                                 | .06      | .20            | .01    | 2.6455 |
| 2   | 2     | 1     | 12    | 1.309009                                 | .12      | .10            | .50    | 2.6390 |
| 2   | 2     | 2     | 21    | 1.308826                                 | .12      | .10            | .50    | 2.6543 |
| 3   | 0     | 0     | 5     | 1.344910                                 |          |                 | 2.6985 |
| 3   | 2     | 0     | 7     | 1.301469                                 |          |                 | 2.6442 |
| 3   | 2     | 1     | 16    | 1.305849                                 |          |                 | 2.6395 |
| 3   | 2     | 2     | 34    | 1.289362                                 |          |                 | 2.6395 |
Likelihood Surface Analysis: Whether the best return model has been determined is not totally clear from the analysis in Table 12. This is because of the data restriction limiting \( L \) to three lags. A significant improvement in the parameterization is apparent when moving from two to three lags. But testing a lag length of four has not been done because of the data restriction. It further appears that no improvement of the fit takes place when increasing \( K_x \) from two to three. As a result, the return model chosen is an \( \text{SP}_r(3, 2, 1) \) parameterization. Table 12 also indicates that the naive model is an \( \text{SP}_r(0, 2, 0) \) specification. Table 13 reveals the unambiguous choice of an \( \text{SP}_x(2, 2, 1) \) parameterization as the best earnings model.

Hypothesis 1: Both the shape and location of the return distribution under each of the returns and earnings model depends upon their respective histories. Consequently, returns are best characterized by a process of conditional moment variation. Therefore, the evidence offered by the sample data is consistent with a market setting that conditionally evaluates informative signals about a liquidating dividend in light of the prior signal history.

The Relative Valuation Information in Accounting Earnings: Table 14 provides the analysis of the relative valuation information in the earnings sequence. The table suggests a considerable improvement in the valuation information revealed by earnings within this industry. Earnings yields are able to capture 26% of the estimated Kullback-Leibler information for discriminating in favor of the best return model over the naive model. The interesting feature within this industry is that both the current shape and location of returns can be explained by two lags of earnings yields. Further, by restricting \( K_x \) to zero as is done in the \( \text{SP}_x(2, 2, 0) \) model, the breakdown between valuation information revealed in location shifts and shape variation can be assessed. Table 14 suggests that 20% of the valuation information in earnings conditions investor beliefs about shape moments. In other words, the greater percentage of valuation information in accounting earnings for this year and last year
Table 14.
Heavy Manufacture & Machinery:
Analysis of the Relative Valuation Information
in Accounting Earnings.

<table>
<thead>
<tr>
<th>Model</th>
<th>$p_θ$</th>
<th>AIC</th>
<th>Cumulative Decrease in AIC</th>
<th>% Cumulative Decrease in AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>$SP_r(0,2,0)$</td>
<td>4</td>
<td>2.6474</td>
<td>0.0000</td>
<td>0.0%</td>
</tr>
<tr>
<td>$SP_x(2,2,0)$</td>
<td>5</td>
<td>2.6455</td>
<td>0.0019</td>
<td>6.0%</td>
</tr>
<tr>
<td>$SP_x(2,2,1)$</td>
<td>12</td>
<td>2.6390</td>
<td>0.0084</td>
<td>26.0%</td>
</tr>
<tr>
<td>$SP_r(3,2,1)$</td>
<td>16</td>
<td>2.6156</td>
<td>0.0318</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

...}

6.1.3 Banking Services

Tables 15 and 16 present the likelihood surfaces for the Banking Services Industry sample.
Table 15.
Banking Services:
Likelihood Surface for
Returns Conditioned on Past Returns.
Sample Size: 377 observations

| L | K_2 | K_r | p_θ | -\frac{1}{2} \log L(r_t|\tilde{r}_{t-1}, \hat{\theta}_r) | p-value | L | K_2 | K_r | AIC^r |
|---|-----|-----|-----|--------------------------------|---------|---|-----|-----|-------|
| 0 | 0   | 0   | 2   | 1.360852                       | .01     | .01| 2.7322|
| 0 | 2   | 0   | 4   | 1.313075                       | .04     | .30| 2.6472|
| 0 | 3   | 0   | 5   | 1.311661                       |         |   | 2.6497|
| 1 | 0   | 0   | 3   | 1.345191                       | .15     | .01| 2.7061|
| 1 | 2   | 0   | 5   | 1.306053                       | .09     | .50| 2.6385|
| 1 | 2   | 1   | 8   | 1.304461                       | .05     | .40| 2.6258|
| 1 | 2   | 2   | 11  | 1.287525                       | .08     |   | 2.6402|
| 1 | 3   | 0   | 6   | 1.305710                       |         |   | 2.6432|
| 1 | 3   | 1   | 10  | 1.289255                       |         |   | 2.6315|
| 2 | 0   | 0   | 4   | 1.341947                       | .50     | .01| 2.7050|
| 2 | 2   | 0   | 6   | 1.302246                       | .20     | .50| 2.6362|
| 2 | 2   | 1   | 12  | 1.279161                       | .01     | .20| 2.6219|
| 2 | 2   | 2   | 21  | 1.266003                       | .30     |   | 2.6434|
| 2 | 3   | 0   | 7   | 1.301131                       |         |   | 2.6393|
| 2 | 3   | 1   | 15  | 1.272837                       |         |   | 2.6252|
| 3 | 0   | 0   | 5   | 1.341830                       | .01     |   | 2.7101|
| 3 | 2   | 0   | 7   | 1.299834                       | .01     |   | 2.6367|
| 3 | 2   | 1   | 16  | 1.260618                       | .50     |   | 2.6061|
| 3 | 2   | 2   | 34  | 1.244577                       |         |   | 2.6694|
Table 16.
Banking Services:
Likelihood Surface for
Returns Conditioned on Past Earnings Yields.
Sample Size: 377 observations.

| $L$ | $K_u$ | $K_x$ | $p_\theta$ | $-\frac{1}{2} \log L(r_t|\tilde{\tau}_{t-1}, \hat{\theta_a})$ | $p$-value | \(L\) | $K_u$ | $K_x$ | AIC$^a$ |
|-----|-------|-------|------------|---------------------------------|----------|------|-------|-------|--------|
| 0   | 0     | 0     | 2          | 1.360952                         | .50      | 2.7322 |
| 1   | 0     | 0     | 3          | 1.359662                         | .50      | .01   | 2.7351 |
| 1   | 2     | 0     | 5          | 1.312771                         | .50      | .50   | .03   | 2.6519 |
| 1   | 2     | 1     | 8          | 1.300356                         | .08      | .40   | .04   | 2.6430 |
| 1   | 2     | 2     | 11         | 1.288984                         | .12      | .01   | 2.6361 |
| 1   | 2     | 3     | 14         | 1.273325                         | .40      | 2.6209 |
| 1   | 2     | 4     | 17         | 1.269627                         |          | 2.6294 |
| 1   | 3     | 0     | 6          | 1.311442                         |          | 2.6546 |
| 1   | 3     | 1     | 10         | 1.298250                         |          | 2.6494 |
| 2   | 0     | 0     | 4          | 1.358825                         |          | 2.7388 |
| 2   | 2     | 0     | 6          | 1.312675                         |          | 2.6570 |
| 2   | 2     | 1     | 12         | 1.289415                         | .07      | 2.6424 |
| 2   | 2     | 2     | 21         | 1.268705                         |          | 2.6488 |
Likelihood Surface Analysis: A similar problem occurred for Banking Services as for Heavy Manufacture & Machinery in determining the best fit to the data for the return model in determining the appropriate lag length. Considering an \( \text{SP}_r(1,2,0) \) model suggests that conditioning the shape on one lag is necessary, but that no increments to the lag length are required. But incrementing \( K_r \) to one then suggests that the lag length be incremented to two. The same phenomena occurs for lag lengths of two. An \( \text{SP}_r(2,2,0) \) specification suggests moving to an \( \text{SP}_r(2,2,1) \) specification which then suggests moving to a lag length of three. It does appear however, that the appropriate values of \( K_z \) and \( K_r \) are two and one respectively. Further, it appears that a model with lag length three is a significantly better fit than a lag length on two. Data limitations restrict increasing the lag length to four. Consequently, an \( \text{SP}_r(3,2,1) \) is chosen as the best model for returns conditioned on past returns. The naive model is again an \( \text{SP}_r(0,2,0) \) specification. An \( \text{SP}_z(1,2,3) \) model is unambiguously chosen from Table 16 for returns conditioned on earnings yields.

Hypothesis 1: The naive model is again rejected as the best characterization of the data for each return process. Therefore, the evidence again supports the hypothesis that the best characterization of the return data is one in which the distribution of returns is conditional on the sequence of prior informative signals.

The Relative Valuation Information in Accounting Earnings: Table 17 provides the analysis of the relative valuation information of accounting earnings within the Banking Services industry. Table 17 indicates a further improvement in the estimated Kullback-Leibler information captured by the best earnings model relative to the best return model when compared with the previous two industries. The interesting point is that no improvement takes place within the earnings model over the naive model because of the conditioning of shape on the earnings history. An \( \text{SP}_z(1,2,0) \) model is worse than the naive model in characterizing the annual return distribution based on the sample data. That is, explaining the mean of next period's
return with the current period earnings yields performs worse, on average, than assuming the mean of next period's return to be the constant estimated from the naive model. The data indicates that conditioning the shape of returns on earnings yields provides a significantly better characterization of the process. This suggests that the valuation information in accounting earnings associates considerably more strongly with the conditioning of higher moments than with location within this industry.

### 6.1.4 Retailing

Tables 18 and 19 show the likelihood surfaces for the Retailing industry.

**Likelihood Surface Analysis:** Exploration of the likelihood surface for the return model yields an unambiguous choice of an $SP_r(1, 3, 0)$ specification. Further, a third order polynomial is necessary to adjust for departures from normality in the naive model as revealed by the $SP_r(0, 3, 0)$ specification. Finally, the likelihood surface for the earnings model yields the optimal choice of an $SP_x(1, 3, 1)$ specification.
Table 18.
Retailing:
Likelihood Surface for Returns Conditioned on Past Returns.
Sample Size: 429 observations

| $L$ | $K_z$ | $K_r$ | $p_\theta$ | $-\frac{1}{2} \log L(r_t|\hat{r}_{t-1}, \hat{\theta}_r)$ | $p$-value | $L$ | $K_z$ | $K_r$ | AIC$^r$ |
|-----|-------|-------|------------|-----------------------------------------------|-----------|-----|-------|-------|---------|
| 0   | 0     | 0     | 2          | 1.316736                                       | .01       | .01 |       | 2.6427 |
| 0   | 2     | 0     | 4          | 1.241028                                       | .01       | .02 |       | 2.5006 |
| 0   | 3     | 0     | 5          | 1.234740                                       | .02       | .02 |       | 2.4927 |
| 1   | 0     | 0     | 3          | 1.305901                                       | .50       | .01 |       | 2.6257 |
| 1   | 2     | 0     | 5          | 1.231300                                       | .50       | .03 | .50   | 2.4859 |
| 1   | 2     | 1     | 8          | 1.304461                                       | .40       | .02 |       | 2.4924 |
| 1   | 3     | 0     | 6          | 1.225408                                       | .50       | .50 | .40   | 2.4788 |
| 1   | 3     | 1     | 10         | 1.221151                                       |          | .02 |       | 2.4882 |
| 1   | 4     | 0     | 7          | 1.224002                                       |          | .02 |       | 2.4806 |
| 2   | 0     | 0     | 4          | 1.305466                                       |          | .01 |       | 2.6894 |
| 2   | 2     | 0     | 6          | 1.230550                                       |          | .03 |       | 2.4889 |
| 2   | 2     | 1     | 12         | 1.221148                                       |          | .02 |       | 2.4981 |
Table 19.
Retailing:
Likelihood Surface for
Returns Conditioned on Past Earnings Yields.
Sample Size: 429 observations.

| $L$ | $K_u$ | $K_x$ | $p_0$ | $-\frac{1}{T} \log L(r_t|\hat{R}_{t-1}, \hat{\theta}_u)$ | $p$-value | $L$ | $K_u$ | $K_x$ | AIC$^a$ |
|-----|-------|-------|-------|---------------------------------|----------|-----|-------|-------|-------|
| 0   | 0     | 0     | 2     | 1.316736                        | .06      | 2.6427 |
| 1   | 0     | 0     | 3     | 1.312651                        | .01      | 2.6392 |
| 1   | 2     | 0     | 5     | 1.237195                        | .20      | 2.4975 |
| 1   | 2     | 1     | 8     | 1.231716                        | .30      | 2.5007 |
| 1   | 3     | 0     | 6     | 1.229831                        | .15      | 2.4875 |
| 1   | 3     | 1     | 10    | 1.218146                        | .07      | 2.4828 |
| 1   | 3     | 2     | 14    | 1.209446                        |          | 2.4841 |
| 1   | 4     | 0     | 6     | 1.227947                        |          | 2.4837 |
| 2   | 0     | 0     | 4     | 1.305677                        |          | 2.6298 |
| 2   | 2     | 0     | 6     | 1.235165                        |          | 2.4983 |
| 2   | 2     | 1     | 12    | 1.225341                        |          | 2.5065 |
| 2   | 3     | 0     | 7     | 1.227249                        |          | 2.4870 |
| 2   | 3     | 1     | 15    | 1.225341                        |          | 2.4819 |
Hypothesis 1: As with all previous industries, the naive model does not figure as either the best return model or earnings model. But, as with Mining, the hypothesis is only partially supported in that the return model exhibits no shape variation conditional on one lag of returns. That is, all moments higher than the mean are constant. The earnings model, on the other hand, is supportive of the hypothesis given both the shape and location of returns are explained by the one lag history of earnings yields.

The Relative Valuation Information in Accounting Earnings: Table 20 provides the analysis applied to previous industries. As Table 20 indicates, the earnings model captures 71% of the estimated Kullback-Leibler information for discriminating in favor of the best return model over the naive model. Therefore, given the method of analysis of information content adopted in the study, the data suggests that within the retailing industry, earnings yields can well characterize the conditional process of observed value change. This valuation information also appears to attach to
conditioning both the shape and location of returns given that explaining the conditional process of returns requires conditioning of all moments with the earnings data. But the relative breakdown between conditioning shape and location is considerably different from other industries. Whereas the history of earnings yields did little to condition the location of returns in prior industries, it does considerably better in Retailing. This leads to a conjecture that earnings bears a different contextual interpretation in its relationship with future return uncertainty. In some settings such as retailing, earnings has information content that associates with all moments of returns, versus Banking Services where only higher moments are explained by earnings. This issue is left as a matter for future research.

6.2 Cross-Industry Analysis

Hypothesis 2  Hypothesis 2 is concerned with observing cross-industry differences in the relative valuation information in accounting earnings on average across the sample time period. Because information content is attributed to conditional variation in return moments, comparing information content across industries requires that at least partial support for Hypothesis 1 is obtained. As the analysis in the previous subsection reported, all industries exhibited at least partial support for Hypothesis 1.

Table 21 summarizes the comparison of the chosen models within each industry sample and, using the AIC, the estimated relative proportion of Kullback-Leibler information for discriminating in favor of the earnings model over the naive model.

The evidence is supportive of Hypothesis 2 in that consistent with the arguments of Chapter III, a cross-industry difference is suggested by the data in how well accounting earnings can characterize the observed change in market valuation on average across the sample period. This study interprets these findings as evidence consistent with contextual differences in how well the accountant’s measure of value change can explain the market process of firm valuation. As Chapter III articulated, the structure of the accountant’s measurement process and the existence of other information
Table 21.
Cross Industry Comparisons
of the Relative Valuation Information
in Accounting Earnings.

<table>
<thead>
<tr>
<th>Industry</th>
<th>Chosen Models</th>
<th>Proportion of Valuation Information in Earnings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mining</td>
<td>$SP_r(2, 2, 0)$ $SP_x(1, 2, 0)$</td>
<td>3.9%</td>
</tr>
<tr>
<td>Heavy Manufacture &amp; Machinery</td>
<td>$SP_r(3, 2, 1)$ $SP_x(2, 2, 1)$</td>
<td>26.0%</td>
</tr>
<tr>
<td>Banking Services</td>
<td>$SP_r(3, 2, 1)$ $SP_x(1, 2, 3)$</td>
<td>64.0%</td>
</tr>
<tr>
<td>Retailing</td>
<td>$SP_r(1, 3, 0)$ $SP_x(1, 3, 1)$</td>
<td>71.0%</td>
</tr>
</tbody>
</table>
sources that impact investor's expectations, suggest that this cross-industry difference should be observed.

The results in Table 21 are also consistent with the loose extreme priors expressed in subsection 5.1 of Chapter V. These stemmed from the length of the production cycle in the chosen industry categories and the relative degrees of uncertainty faced by accountants in measuring earnings for a twelve month period within these categories. Therefore, the evidence in support of Hypothesis 2 is consistent with these assertions.

Another interesting observation from Table 21 is that the length of conditioning history for the earnings models is always less than or equal to the length of history in the return model. Although no strong priors were held about what these values of \( L \) should be, one possible interpretation lies in the lead-lag results of Beaver, Lambert and Morse [1980], Collins and Kothari [1989] and Kothari and Sloan [1990]. One of the conclusions in these studies is that prices lead earnings based on the hypothesis that earnings is a non-timely information source for valuation, whereas price impounds all timely information. Kothari and Sloan [1990] conclude that prices lead earnings by three years on average. Within the context of this study, the non-timeliness of earnings is interpreted as an informational restriction inherent in accounting earnings. It is possible that the conditioning information set in the earnings model is always relatively out of date when compared with the full information set measured here by the history of past returns. It is also noticeable that the model in which earnings was concluded to have most valuation information (i.e., Retailing) is the model in which the lag lengths of the models are equal. Therefore, it is posited that one explanation for this result may be because of the lead-lag nature of earnings and prices documented in previous research.
6.3 Summary of Empirical Findings

The empirical findings of this study are summarized as follows:

1. Analysis of the data suggests a market environment consistent with the use of information as a dynamic resource that continuously updates expectations about some liquidating dividend. This is evidenced by observing a return process whose stochastic properties at any given time point are conditional on measures of the informative signals existing to that time point.

2. Accounting earnings as one source of informative signals can characterize these stochastic properties. But the study finds that:
   - This ability to characterize the conditional moments of returns varies depending upon production/investment context, which is interpreted as evidence consistent with contextual variation in the valuation information conveyed by accounting earnings.
   - Accounting earnings as an information source appears to be associated with different return moments depending upon the economic context. This implies that in some economic circumstances accounting may be more informative about the higher moments of future value assessments as distinct from merely the expected value of future returns. Further exploration of this issue is left as a matter for future research.\(^{21}\)

3. A preliminary observation suggests that the findings appear consistent with previous research on the lead-lag relationship between accounting earnings and prices.

\(^{21}\)This of course potentially suggests an answer to Lev's [1989] criticisms concerning the apparent lack of "usefulness" in accounting earnings.
6.4 Limitations

The above conclusions come with a number of caveats. The first major limitation is that the results are based on an assumption that the sample data within each industry is homogeneous with respect to production/investment circumstances. In other words, it is assumed that the cross-industry variation observed is the result of an underlying difference in economic characteristics that associate with the ability of accounting earnings to capture valuation relevant information, and not just from sampling variation. Closely related to this caveat is that these noted differences are not attributable to other economic contextual issues such as macroeconomic circumstances affecting each industry in some systematically different way. In other words, industry context is not highly correlated with some other macroeconomic variable that is "true" explanator of the noted cross-sample differences.

Secondly, a number of measurement assumptions with respect to information have been made in developing the analysis. These are that past returns can be used to model the effect of market participants evaluation of all informative signals, and that accounting earnings is invertible in its valuation relevant signals. Both of these assumptions are necessary features for interpretation of the analysis. An extension to this study might involve empirically testing the return model relative to other return models to establish the robustness of the conclusions drawn here.

Finally, it has been assumed that observing conditional variation in return moments is the outcome market participants continual assessments of information. But, as Antle, Demski and Ryan [1989] point out, and as discussed in subsection 3.2.3 of Chapter III, observing no conditional variation in a moment does not imply no information content for a given period of time, since the informative effect of a given signal may manifest at a future time point upon concatenation with some future signal. The study has treated this case as somewhat pathological in the sense that given the degree of cross-sectional aggregation that has taken place within industries, it is unlikely that all firms at a given time point exhibit this phenomena. Therefore,
even though some models exhibited no conditional variation in shape for the sample time period, it is assumed that this is not indicative of potential information content awaiting concatenation with future signals. In other words, the sample time period is assumed to be representative of the interplay of informative signals across time, and so captures the information content of accounting earnings.

6.5 Extensions

A number of extensions are suggested. The first is an extension to expand the accounting source to include other financial statement information. Recent work by Ou and Penman [1989] suggests that financial statement variables provide useful information in predicting return swings. What is suggested is an analysis to observe whether significant improvement in the earnings model results by expanding the conditioning variables to a vector of financial statement variables. Further, it can be questioned whether there is a difference observed in how return moments associate with these variables, as distinct from the earnings model used in this study.

Second, as mentioned in subsection 6.4 above, some further exploration into the differing cross-sectional moment effects of accounting information can be undertaken. Finally, the reason why accounting is informationally restricted has been argued to result from accounting structure and the effect of other information. No specific analysis has been undertaken to isolate the relative association of each of these variables. One extension is to consider a reporting circumstance in which only accounting information is available, and so potentially isolate the effect of accounting structure. Such a circumstance is difficult to envision. Possibly the closest situation is that of initial public offerings. In these circumstances it is possible to argue that the potential exists to minimize the other information component.
LIST OF REFERENCES


APPENDIX A
Sample Data for the Mining Industry

Table 22 provides a detail breakdown of the firms comprising the Mining industry sample. Listed is the CUSIP identifier from the CRSP tape, the company name as recorded on CRSP, the 2-Digit SIC code, and the number of the sample observation.

Table 22.
Sample Companies for the Mining Industry.

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<tr>
<th>CUSIP</th>
<th>COMPANY NAME</th>
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<td>Amoco Corp</td>
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<td>Arkla Inc</td>
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<td>04924930</td>
<td>Atlas Cons Mng &amp; Dev Corp</td>
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<td>06968910</td>
<td>Baruch Foster Corp</td>
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<td>11088940</td>
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<td>74741010</td>
<td>Quaker State Corp</td>
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<td>77938210</td>
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<td>98991710</td>
<td>Zemex Corp</td>
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Table 23 provides a detail breakdown of the firms comprising the sample for Heavy Manufacture & Machinery. Listed is the CUSIP identifier from the CRSP tape, the company name as recorded on CRSP, the 2-Digit SIC code, and the number of the sample observation.

Table 23.
Sample Companies for Heavy Manufacture & Machinery.

<table>
<thead>
<tr>
<th>CUSIP</th>
<th>COMPANY NAME</th>
<th>2-Digit SIC</th>
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<td>00462610</td>
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<td>Alcan Aluminium Ltd</td>
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<td>Allied Prods Corp</td>
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<td>Ampco-Pittsburgh Corp</td>
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<td>Brown &amp; Sharpe Mfg Co</td>
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<td>C C X Inc</td>
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APPENDIX C
Sample Data for Banking Services

Table 24 provides a detail breakdown of the firms comprising the Banking Services sample. Listed is the CUSIP identifier from the CRSP tape, the company name as recorded on CRSP, the 2-Digit SIC code, and the number of the sample observation.

Table 24.
Sample Companies for Banking Services.

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Table 25 provides a detail breakdown of the firms comprising the Retailing sample. Listed is the CUSIP identifier from the CRSP tape, the company name as recorded on CRSP, the 2-Digit SIC code, and the number of the sample observation.

Table 25.
Sample Companies for Retailing.

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