THE PREDICTION OF ROE: FUNDAMENTAL SIGNALS, ACCOUNTING RECOGNITION, AND INDUSTRY CHARACTERISTICS

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Comments welcome.

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Abstract

We focus on the prediction of book return-on-equity [ROE]. In particular, based on recent accounting and industrial organization literature, we compare the predictive power for ROE of three types of information variables: 1) fundamental signals in the financial statements aggregated as a fundamental score of the firm, 2) accounting recognition variables based on the book-to-market [BTM] ratio of the firm (delayed and biased recognition), and 3) variables that measure the characteristics of the firm's industry (concentration and barriers-to-entry) and the market share of the company.

The analyses show that the three sets of information variables considered contain variables that provide predictive power for future ROE incremental to current ROE. First, the aggregated fundamental signals predict future ROE up until four years into the future. Second, the accounting recognition variables also predict future ROE beyond current ROE. However, the two components of BTM that capture accounting recognition provide different information for future ROE. Delayed recognition is positively related to future ROE and biased recognition negatively. Third, market share predicts future ROE in the presence of the other information variables and current ROE up until three years into the future. In contrast, concentration and barriers-to-entry provide no predictive power.

Overall, the conclusion of our analyses is that all three sets of variables capture some piece of information about future ROE incremental to current ROE and to each other.

1 Introduction.

In this paper we focus on the prediction of book return-on-equity or *ROE*. *ROE* combines earnings and book value of equity and is therefore a key summary measure of the financial statements. In particular *ROE* is a central measure of a firm's profitability and as such it is often considered the starting point of a systematic analysis of the profitability of the firm (see Palepu et al., 1996). It is therefore not surprising that previous accounting research has examined the behavior of *ROE*.[1] The role of *ROE* in equity valuation is the starting point of our analysis. Based on the framework developed by Ohlson (1995), Penman (1991) and Bernard (1994) are the first to show that the price of a stock is a linear function of book value per share and a term that captures expected future *ROE*. The prediction of future *ROE* therefore is central in the accounting-based valuation literature.

Our study contributes to this literature by focusing on the role of different types of information variables for the prediction of *ROE*. In particular, we consider three distinct sets of information variables that relate to future *ROE*: 1) fundamental signals; 2) variables that capture accounting recognition; and 3) variables that capture industry characteristics. Our (preliminary) results show that variables from each information set have predictive power for future *ROE* incremental to current *ROE* for some period into the future.

Penman (1991) provides us with the motivation for inclusion of our first set of information variables in the research design. Based on the link between price, book value and future *ROE*, he states that fundamental analysis of the financial statements of the firm is characterized as observing information that projects future *ROE*. Accordingly, we base our first information variable on the work by Lev and Thiagarajan (1993) [hereafter, LT] and Abarbanell and Bushee (1997) [hereafter, AB] that studies the relation between a set of fundamental signals in the financial statements of the firm and current security returns and future earnings changes. In a manner consistent with LT and AB, we aggregate the fundamental signals into a fundamental score of the firm and evaluate its predictive power for *ROE*.

Our second set of information variables is based on the literature that studies the predictive power of *BTM* for future *ROE*. Penman (1991), Bernard (1994) and Penman (1996) show

[1] Early studies include Beaver 1970, Lookabill 1976, and Freeman et al. 1982. Other studies willbe mentioned throughout the text.

that the book-to-market ratio [BTM] of the firm predicts future ROE beyond current ROE. However, Bernard (1994) concludes that BTM adds little predictive power beyond current ROE. Beaver and Ryan (1996) [hereafter, BR] extend this work by showing that components of BTM, that capture delayed and biased accounting recognition, predict future ROE beyond current ROE. We therefore include these components of BTM in our research design as our second information variable set.

We also extend the previous work in the accounting literature by considering a third set of information variables that capture industry characteristics. In particular, we include information variables in the analysis that capture concentration and barriers-to-entry in the firm's industry and the market share of the firm. These variables have been studied in the industrial organization [IO] literature as determinants of the profitability of firms. This paper makes a contribution by considering these industry information variables jointly with the accounting variables. Economic notions of profitability are often measured with accounting measures in the IO literature. However, IO researchers generally do not address the impact of accounting recognition rules in GAAP on the ability of accounting numbers to serve as proxies for economic concepts. Similarly, accounting research generally does not consider variables that capture industry characteristics as information variables for future ROE. However, the relation between industry characteristics and the pattern of future ROE is often invoked to address the terminal value problem in the accounting-based valuation equations. Our analysis documents the relation between future ROE and the industry characteristics.

We carry out two sets of analyses. First, we study the predictive power for future ROE of the information variables on a univariate basis. Second, we carry out a multivariate regression analysis to evaluate which information variables predict future ROE, incremental to current ROE.

The results from the univariate analyses show that most variables predict future ROE in a statistically significant way up to some period into the future. The weakest results are obtained for the industry concentration and barriers-to-entry variables. These variables exhibit little or no predictive power for future ROE. In contrast, on a univariate basis, market share is a very strong predictor of future ROE.

The results from the multivariate regression analyses show confirm that current ROE is a strong

predictor of future ROE and that ROE exhibits a mean-reversing pattern. More importantly, the results show that the three sets of information variables considered in this study contain variables that provide predictive power for future ROE incremental to current ROE. First, the aggregated fundamental signals, or $FSCORE$, predict future ROE up until four years into the future. This corroborates and extends previous results presented by LT (1993) and AB (1997) by establishing an explicit link between the fundamental signals and future ROE. Second, the accounting recognition variables identified by BR (1996) also predict future ROE beyond current ROE. However, the two components of BTM that capture accounting recognition provide different information for future ROE. The results suggest that DR reflects transitory elements in earnings and is inversely related to earnings-per-share. As a consequence, DR exhibits a significant positive relation to future ROE. The BR component of BTM however is persistently and negatively related to future ROE. Of the two components, DR exhibits the strongest predictive power for future ROE in the multivariate context. The information captured by DR is as important as or more important than the information in current ROE for the prediction of ROE from three years into the future onwards. Surprisingly, in the multivariate context, BR shows a relatively weak predictive power for future ROE. Although BR predicts ROE very strongly in a univariate context, its predictive power in the multivariate regression is diminished by the presence of the other variables. Third, market share or MS predicts future ROE in the presence of the other information variables and current ROE up until three years into the future. In contrast, concentration and barriers-to-entry provide no predictive power. In addition, it seems that $SIZE$, a control variable in the regressions, can be interpreted as a proxy for economies-of-scale as it captures some of the predictive power of MS.

To summarize, our analyses lead to three findings. First, the financial statements of firms contain fundamental information about the future profitability of the firm, not reflected in current profitability. Second, the variables based on the BTM that capture the effects of accounting recognition on BTM help to predict of future ROE in the presence of current ROE. However, the accounting recognition variables are associated differently with future ROE. Third, the results for the industry characteristics variables are mixed. Concentration and barriers-to-entry provide little or no predictive power for future ROE whereas market share proves to be a strong predictor. This is consistent with recent claims made in the IO literature that market share is

a more important determinant of a firm's profitability than the concentration and barriers-to-entry of the industry in which it operates.

Overall, the conclusion of our analyses is that all three sets of variables capture some piece of information about future ROE incremental to current ROE and to each other.

The remainder of this paper is organized as follows. The following section presents the motivation for the prediction of ROE and discusses the three sets of information variables we include in the research design. The next section defines the empirical proxies we use and presents the research design. Section 4 discusses data and sample. Section 5 presents the results and the last section concludes.

2 The Prediction of ROE.

The starting point of this study is the role of ROE in equity valuation. Following Penman (1991) and Bernard (1994), we focus on the link between current market value of equity or price of the firm and current and future ROE.[2] First, Ohlson (1995) and FO (1995) derive a valuation equation where price is a linear function of accounting variables book value and (expected) abnormal earnings:

$$P_t = bv_t + \sum_{\tau=1}^{\infty}(1+r)^{-\tau}E_t[ni^a_{t+\tau}] \tag{1}$$

where P_t is the share price of the firm at time t, ni_t are the earnings per share of the firm at time t, bv_t is the book value per share of the firm at time t, and r is required return on equity (considered non-stochastic and identical across firms). ni^a_t are abnormal earnings per share of the firm at time t, defined as $ni_t - rbv_{t-1}$.[3]

We define ROE as net income divided by beginning-of-period book value, or $\frac{ni_t}{bv_{t-1}}$, and rewrite the original valuation equation (1) as follows (see Bernard, 1994):

$$P_t = bv_t + \sum_{\tau=1}^{\infty}(1+r)^{-\tau}E_t[(ROE_{t+\tau} - r)bv_{t+\tau-1}] \tag{2}$$

[2]Price expresses market value of the firm on a per-share basis. We carry out our empirical analyses on a per-share basis to mitigate possible problems of heteroscedacity.

[3]The valuation equation is based on the traditional dividend discount model, the clean surplus relation, and the definition of abnormal earnings. We refer the reader for more details to Ohlson (1995) and FO (1995).

By dividing both sides by bv_t, equation (2) can be expressed as follows:

$$\frac{P_t}{bv_t} = 1 + \sum_{\tau=1}^{\infty} \frac{1}{(1+r)^{\tau}} E_t[(ROE_{t+\tau} - r)\frac{b_{t+\tau-1}}{b_t}] \tag{3}$$

In other words, eq. (3) expresses the price-to-book $[PB]$ ratio in terms of future ROE and growth in book value (i.e., $\frac{b_{t+\tau-1}}{b_t}$). Assuming a dividend payout ratio in the future, growth in book value can be inferred from future ROE by imposing the clean surplus relation on the predicted ROE (see Frankel and Lee, 1996). In other words, this allows to express eq. (3) solely in terms of future ROE.

The research question asked in this paper is how observable data can be used to predict ROE. Two approaches have been followed in previous literature to predict ROE. First, researchers have used analysts' forecasts of earnings and book value to construct future ROE (see for example Bernard 1995, and Frankel and Lee 1996). However, relying on analysts' forecasts does not provide insights into the relative contribution of accounting and other variables to the prediction of future ROE. We therefore opt to follow a second approach and focus on the prediction of future ROE directly from a set of information variables.

In particular, we confront the predictive power for ROE of three different sets of information variables: 1) fundamental signals; 2) accounting recognition variables; 3) industry characteristics variables. The choice of the first two sets is based on previous accounting research. The first set is comprised of fundamental signals of a firm's profitability, identified by LT (1993) and AB (1997). The second set contains variables that capture important features of the accounting model, namely delayed and biased recognition (BR, 1996). The third set of information variables is based on the IO literature and relates to the characteristics of the industry in which the firm operates.

As previous studies have demonstrated the ability of current ROE to predict future ROE, we adopt the approach of using current ROE as a benchmark information variable.[4] The main tests in this study will therefore measure the predictive power of certain information variables *incremental* to current ROE.

The next sections discuss these three sets of information variables as they relate to the

[4]As mentioned, a number of previous studies have demonstrated the mean-reversing character of ROE (see for example table 1 in Penman, 1991). Recently, Fairfield et al. (1996) use forecasts based on current ROE as a benchmark to evaluate other forecasts based on disaggregated earnings.

prediction of ROE.

2.1 Fundamental signals.

Because future ROE fulfills a central role in accounting valuation, Penman (1991) points out that the objective of financial statement analysis is to identify information that predicts future ROE. Our first type of information variable therefore captures the fundamentals in the financial statements of the firm. We base our choice of variable on the work of LT (1993) and AB (1997). Based on a guided analysis of the financial statements, LT (1993) identify a number of fundamental information signals that capture persistence in earnings. The results of their analyses indicate that a fundamental score of the company, i.e. an aggregate of the individual fundamental signals, exhibits a statistically significant relation with the earnings response coefficient. AB (1997) extend the research of LT in an important way by linking the fundamental signals directly to future earnings changes, rather than to comtemporaneous returns (AB, p. 1). The results in AB confirm that the fundamental signals have incremental explanatory power for future earnings changes relative to current-year earnings.[5]

We use the set of firm-specific fundamental signals identified by LT and AB as our first set of information variables for future ROE. The joint evidence in LT and AB shows that the fundamental signals capture value-relevant events beyond current earnings and that this information is impounded in the stock return. This suggests that the information in the fundamental signals might both explain current profitability and predict future profitability beyond current profitability.

2.2 Accounting recognition.

Next, we include a set of accounting recognition information variables in the research design for two reasons. First, the computation on the fundamental signals does not consider the impact of accounting rules on their ability predict future ROE. The previous discussion assumes implicitly that value-relevant events are reflected in the financial statements of companies in a timely and

[5]In addition, AB show that analysts' forecast revisions do not impound all the information about future earnings comprised in these fundamental signals. However, returns-based tests suggest that the fundamental signals exhibit incremental explanatory power for returns relative to analysts' forecast revisions. This would imply that investors recognize the fact that analysts' forecast revisions do not capture all the value-relevant information in the fundamentals. In addition to the reason given above, this latter result leads us to focus on *statistical* prediction of ROE, rather than prediction based on analysts' forecasts.

unbiased way. However, accounting numbers are derived within the boundaries of current GAAP, with its conventions and rules regarding the recognition of economic events.[6] As a consequence, accounting recognition rules might influence and even impair the predictive power of current fundamental signal for future ROE. Second, the time series pattern of ROE is also influenced by accounting recognition rules.

We follow the approach of BR (1996) and define the accounting recognition variables based on the divergence between market value and book value of the firm. BR explain how the ratio of these two measures, the book-to market ratio [BTM] or the inverse of the PB, can be statistically decomposed to reveal two important features of accounting recognition: delayed and biased recognition. *Delayed* recognition follows from the historical cost principle in GAAP and causes the BTM ratio to deviate temporarily from *one* as unrealized gains and losses on assets and liabilities are recognized in the accounting system over the remaining life of assets and liabilities whereas they are reflected in market values immediately. *Biased* recognition causes BTM to be permanently different from *one*. Biased recognition follows from the conservative accounting valuation of existing assets and liabilities or the non-recognition of positive net present value projects.[7]

BR show that that the two components of BTM are useful in predicting future ROE beyond current ROE.[8] There exists a strong negative association between delayed recognition and ROE. This association decreases over a period of five years as book value slowly catches up with market value of equity. The biased recognition component also exhibits a strong negative association with future ROE. However, this association decreases very slowly over the future years. In other words, the association between biased recognition and future ROE persists.

In addition to reflecting the conservative accounting recognition of the firm, the biased recognition component also contains information about positive net present value projects of the firm not reflected in the recognized net assets. By design, this information is *incremental* to the information captured by the delayed recognition component (see below). By including

[6]In general, *accounting recognition* is the mechanism that translates transactions and economic events to accounting numbers. The Statement of Financial Accounting Concepts (SFAC) no.3 of the FASB defines accounting recognition as the process of formally recording or incorporating an item in the accounts and financial statements of an entity.

[7]An example of this permanent biased recognition relates to GAAP for R & D. Firm's are required to expense R&D so that there is no intangible asset on the balance sheet representing R&D capital, which may be a firm's most valuable asset.

[8]This can be inferred from valuation eq. (3).

the biased recognition variable in the research design together with the fundamental information variables, we address the empirical question of whether the information in the biased recognition component is captured by the fundamental information variables or vice versa.

2.3 Industry characteristics.

The third set of information variables is based on results from the industrial organization literature. Since Bain (1956) this literature has studied how industry structure elements influence the profit generating process of firms. Industrial economists provide a theoretical framework for the evolution of profits and show that profits result from a firm's interaction with market forces such as competitors, consumers' demand, and suppliers. In particular, the *structure-conduct-performance* [SCP] relation as introduced by Bain states that a firm's performance is determined by its access to environmental resources, as it competes for sales, capital, and workforce. The SCP paradigm is based on the *concentration-collusion* doctrine and supposes that a one-way chain of causation runs from *structure* (e.g., the level of firm concentration in an industry) to *conduct* (the degree of collusion), and from conduct to *performance* (profitability).[9] In the extreme, the SCP relation presumes that what is important in explaining a firm's profits are the characteristics of the industries in which it sells. Thus, all firms within an industry should have the same profit rate or should at least converge to a common industry profit rate.[10] *Concentration* is considered a significant dimension of industry structure and refers to the degree of control of economic activity of large firms in an industry.[11]

In the SCP paradigm, industry structure is also explained by the presence of certain *barriers-to-entry* in addition to concentration *per se*. Barriers-to-entry are the advantages of incumbents in an industry over potential entrants. They are reflected in the extent to which incumbents can persistently raise their prices above a competitive level without attracting new firms to enter the industry. Siegfried and Evans (1994) review 70 empirical studies of entry patterns

[9]More recently, the IO literature reformulated many arguments from the traditional SCP context into an explicit game theoretical setting. However, the results of game theoretic analyses depend delicately on a range of factors that are impossible to identify or to proxy empirically (e.g., the formulation of the underlying game). Traditional cross-industry research has focused on empirical regularities and has provided some fairly robust results that hold across a broad range of model specifications (Sutton, 1991).

[10]As Biddle and Seow (1991) point out, the link between market structure and profitability has served as the basis for the concentration doctrine underlying the U.S. antitrust regulation.

[11]In other words, a measure of concentration captures the size distribution of competitors and is therefore a direct measures of the degree of oligopoly in an industry.

done over the last two decades. Entry increases competition and induces incumbent firms to operate as efficiently as possible. The perceived threat of entry may encourage incumbent firms to behave as if they are in a competitive market even when they are not. High past profits and growing demand in an industry attract entrants. Entry deterrent actions include heavy advertising, patenting, price cut threatening, and keeping excess capacity to meet all expected demand.[12] The consideration of barriers-to-entry introduces a dynamic element in the static SCP setting. Concentration of the industry is a necessary but not sufficient condition for above normal profits. If barriers-to-entry are low, the profit rates in the industry will be driven down by the arrival of new entrants in the industry. In other words, where barriers-to-entry are high, high concentration of industry might lead to a persistence of above normal profits (see the discussion in chapter 1 of Mueller, 1990). This implies that the *interaction* of concentration and barriers-to-entry of the industry are the determinant of the profitability of the firm.

The IO literature has also been explaining profitability in terms of a firm's *market share* in its industry. Demsetz (1973) was one of the first to argue that products are more efficiently produced by firms possessing a large market share, because they can produce at lower unit costs than smaller firms. Market share can therefore be interpreted as the effect of scale-related efficiencies. It can also be viewed as a measure of market power related to quality differences, patent positions, and price discrimination. The IO literature generally posits a positive relationship between market share and profitability of the firm. Several empirical studies even find that concentration is insignificant or negatively correlated with profitability when market share is included in the analysis (Mueller, 1986). Also, whereas industry concentration and industry barriers-to-entry are industry-wide characteristics, market share is a firm-specific variable.

In addition to finding proxies for market structure characteristics, the empirical IO research faces an important measurement issue related to accounting. Generally, IO researchers measure the economic concept of profit with accounting proxies. However, as profitability measures based on accounting numbers are subject to the limitations of accounting recognition, this possible introduces considerable measurement error into the analysis. Studies that address this

[12]Siegfried and Evans (1994) make a distinction between *structural* and *behavioral* barriers. The former exist because of the long-term, stable structural characteristics of an industry, not because of discretionary conduct by incumbent firms. Examples of this kind of barrier are: absolute cost advantages over potential entrants (this can be related to capital intensity) and economies of scale. Behavioral barriers are based on the behavior of incumbent firms: they threaten or behave in such a way that they discourage other firms from entering the market.

problem conclude that either accounting data provide poor measures of economic market values (e.g., Fisher and McGowan 1983, or Benston 1985) or that the choice of profit measure and its corresponding proxy greatly influences the results of the analysis (e.g., Amato and Wilder, 1995). Although empirical researchers in IO apparently seem to be aware of the existence of measurement problems in accounting numbers, they typically do not study how the idiosyncracies of GAAP influence the ability of accounting numbers to serve as proxies for economic concepts.[13,14]

On the other hand, few accounting studies consider industry characteristics in their studies of the behavior or persistence of earnings. One example is the study by Lev (1983) who states that the time-series properties of accounting numbers should be conditional on known relationships between environmental and firm-specific economic factors. According to Lev's study, economic factors that affect earnings are barriers-to-entry, firm size, capital intensity, and product type. Another example is Biddle and Seow (1991) who find that earnings response coefficients are a function of the operating and structural characteristics of a firm's industry.

We contribute to both accounting and empirical IO research by providing evidence related to two questions. First, do variables that reflect the structure of a firm's industry or the relative importance of the firm within the industry help predict future profitability relative to current profitability? Second, is the industry information about the firms captured by either the fundamental information variables or the accounting recognition variables? In other words, do the industry information variables have predictive power for future ROE in the presence of the two

[13]One exception is the study by Van Breda (1981), who views the accounting system as a series of *filters* through which economic events are translated into accounting numbers such as operating costs, sales, profits. Because of this filtering process, the accounting numbers exhibit a different response pattern to economic events then market values. The impact on profitability measures is such that although the return on the market value of equity adjusts swiftly in response to economic events, the accounting rate of return adjusts slowly. Apart from Van Breda (1981), no other study in the IO literature has explicitly taken accounting biases into account in the research design.

[14]The empirical IO literature also faces the problem of defining industries using SIC codes that reflect the product being produced (i.e. supply side characteristic). Therefore they do not often correspond to the boundaries of economically meaningful markets (Bloch 1994). For example, a computer hardware firm could dominate the national market, but its true competitors could actually be firms from other nations that are not incorporated in the national SIC code. The use of geographic markets within a well-defined industry may provide better economic market constructs than the use of a cross-section of SIC industries (Amel, 1991). Because we lack consistent and complete geographical data for the sample period, we base our industry grouping on similarity of national output markets as in Biddle and Seow (1991). Kahle and Walkling (1996) point out a number of problems with using the SIC classification, e.g., the differences between CRSP and Compustat SICs and their effects in financial research. We discuss our industry definitions in section 4. Also, concentration measures based on industries do not account for the fact that large firms operate in different industries. As conglomerates become more important in the economy compared to the traditional focused firms, concentration measures become increasingly less relevant as measures of economic power (Dugger, 1985). One way to address this issue would be to use segment information of firms and this might prove an interesting avenue for future research.

sets of accounting-based information variables?

The next section presents the empirical proxies for the information variables and the research design.

3 Empirical Proxies and Research Design.

3.1 Empirical proxies.

Fundamental signals.

We consider the same fundamental signals as in AB and correspondingly adopt the definitions provided by AB in their table 1 (AB, p. 4). The fundamental signals focus on inventory, accounts receivable, capital expenditure, gross margin, selling and administrative expenses, effective tax rate, earnings quality, audit qualification, and labor force. The definitions of the signals are presented in Appendix A. The signals are defined such that a negative value indicates good news, i.e. predicts a future earnings increase. For the sake of parsimony and consistent with LT and AB, we aggregate the individual signals into a fundamental score, $FSCORE$, by dichotimizing the values of the signals: a negative (positive) value is assigned a value of zero (one). $FSCORE$ is then computed as the sum of the assigned values: a low value of $FSCORE$ indicates good news for future profitability.

Accounting recognition.

To obtain the accounting recognition variables, we follow the methodology presented by BR. First, we estimate the following fixed effects two-way error component model regression of BTM on the current and six lagged security returns:

$$BTM_{t,i} = \alpha_t + \alpha_i + \sum_{j=0}^{6} \beta_j \cdot R_{t-j,i} + \varepsilon_{t,i} \tag{4}$$

where α_t = time-effect, captures downward trend in median BTM,

α_i = firm-effect, expresses biased recognition, and

$R_{t,i}$ = security return of firm i in year t.

The two recognition components are then derived from the explained firm-specific variation in the BTM ratio: the firm-effect in equation (4), α_i, represents the biased recognition component,

and the projection of BTM on the span of the returns ignoring the fixed effects gives the delayed recognition component. BR (biased recognition) and DR (delayed recognition) are defined as follows:

$$BR = \alpha_i = (\overline{BTM}_{\cdot,i} - \overline{\overline{BTM}}) - \sum_{j=0}^{6} \hat{\beta}_j \cdot (\overline{R}_{\cdot,i} - \overline{\overline{R}}) ,$$

$$DR = \sum_{j=0}^{6} \hat{\beta}_j \cdot (R_{t-j,i} - \overline{R}_{t-j,\cdot} - \overline{R}_{\cdot,i} + \overline{\overline{R}}) ,$$

where $\overline{R}_{t-j,\cdot} = \frac{1}{n} \sum_{i=1}^{n} R_{t-j,i}$, time mean of R,

$\overline{R}_{\cdot,i} = \frac{1}{T} \sum_{t=1}^{T} R_{t-j,i}$, firm mean of R,

$\overline{\overline{R}} = \frac{1}{nT} \sum_{t=1}^{T} \frac{1}{n} \sum_{i=1}^{n} R_{t-j,i}$, overall mean of R, and

$\hat{\beta}_j$ = the jth return coefficient estimated in equation (4), and

analogous definitions for $\overline{BTM}_{\cdot,i}$ and $\overline{\overline{BTM}}$.

As a reminder BR represents the variation in BTM that persists for an individual firm through time, where DR represents the variation in BTM due to unrecognized past market returns, ignoring the portion of variation that is already captured in the fixed effects (time and firm effect in equation (4). Notice that a time-effect is included in the equation to capture the evolution of BTM over the time period studied.

Industry characteristics.

Based on the discussion about industry characteristics, we include industry information variables that measure the concentration and barriers-to-entry of the industries and a variable that measures the market share of firms.

The first variable measures the concentration in the industry. The IO literature uses a multitude of concentration indices.[15] All these indices are based on some indicator of activity or size of the firms in the industry. We base our industry measures on the relative *sales* of the firms in the industry as we believe that sales is the most adequate accounting proxy for the activity level of the firm.[16] Based on the sales of each company, we compute the *Herfindahl-Hirschman*

[15]Chakravarty (1995) mentions the k-firm concentration index, the Linda index, the Herfindahl-Hirschman index, Shannon's entropy measure, and the Gini-index.

[16]See also Dechow et al. (1995). Sales might be more adequate as a descriptor of real activity of a firm than total assets or earnings because it is likely to be less influenced by accounting manipulation. In addition, sales are (generally) a positive number.

Index [HHI] for each industry. We choose HHI as a summary measure of market concentration because it reflects both the number of firms in the industry, N, and the concentration of output of all firms in the industry, by incorporating the relative size (market share, MS_i) (Rhoades, 1993):

$$HHI = \sum_{i=1}^{N} MS_i^2.$$

As a result of squaring the market shares, the HHI places heavier weight on firms with large market shares. Chakravarty (1995) discusses some formal criteria to judge concentration measures, and HHI satisfies all these desirable features.[17]

Next, we measure the barriers-to-entry of the different industries. Lev (1983) and Biddle and Seow (1991) classify the industries in their sample in two groups based on work by Palmer (1973). In other words, they introduce barriers-to-entry as a dummy variable in their research design. We follow a different approach by measuring barriers-to-entry via proxies for the capital intensity of the industry. There exists empirical evidence in the IO literature that the cost of fixed capital required to operate a minimum efficient scale plant has a strong negative effect on entry (Siegfried and Evans, 1994, p.130). Otherwise put, capital intensity is a way of expressing the extent to which firms make binding commitments of resources. Firms competing in capital-intensive industries typically have to bear large, unrecoverable expenses in advance of actual production. Capital intensity is an expression of capital commitment and can be an important entry deterrent. We measure capital intensity with the median ratio of property, plant, and equipment as a percentage of total assets (a measure of the firm's capital commitment) per industry:

$$PPETA = \frac{\textit{property, plant \& equipment}}{\textit{total assets}}.$$

We also define a variable that captures the *interaction* between concentration and barriers-to-entry, namely $INTIND$. $INTIND$ is the product of HHI and $PPETA$ per industry.

Finally, we include the market share of each of the sample firms in their industry in the set

[17]These criteria are: homogeneity (measures should only depend on output shares, not on absolute levels), symmetry, output transfer principle (concentration decreases if some output is transferred from a large firm to a small firm, without reversing their ranking), zero output independence (deletion of a firm with zero or close to zero output does not change the level of concentration), merger principle (concentration increases when two firms merge), and continuity (a continuous variable) .

of industry information variables. We measure market share of a firm, MS, as the ratio of its sales to the total sales of its industry.

Control variables.

Apart from current ROE and the three main categories of variables of interest, we also include two control variables in the analyses.

First, we include a proxy for risk. Although Penman (1991) suggests that ROE should be interpreted as a measure of profitability and not risk, it can be expected that the risk of the firm will have an impact on ROE. This can be seen from the traditional Du Pont formula that links ROE to ROA and leverage: as leverage and therefore risk increases, ROE increases (see also Penman 1991). We measure leverage ($FINLEV$) as the ratio of book value to total assets:

$$FINLEV = \frac{\textit{book value of equity}}{\textit{total assets}} .$$

Second, we include a control for $SIZE$ in the analyses. $SIZE$ can be interpreted as a catch-all proxy for several concepts. $SIZE$ is often used in the accounting literature as a proxy for risk, or growth (see Lev, 1983). In the industrial organizations literature, researchers have used $SIZE$ as a proxy for barriers-to-entry. $SIZE$ can reflect economies of scale, that may impede entry if potential entrants must enter with large output to take advantage of large scale production cost savings (Siegfried and Evans, 1994, p.132). Also, $SIZE$ is sometimes seen as a barrier-to-entry for another reason. Absolute size reflects a firm's ability to exert political pressure or lobby power, and win profitable favors from local or national governments (Mueller, 1986, p. 138). We measure $SIZE$ as the market value of the firm.[18]

3.2 Research Design.

We carry out two sets of tests. First, we perform univariate analyses to assess the individual predictive power of each information variable for future ROE. As in Frankel and Lee (1995) and BR (1996) we follow a portfolio approach to specify the expectations of ROE conditional upon the respective information variables. We form five portfolios based on the quintiles of the distribution of each information variable and we calculate the median ROE for each portfolio.

[18]We also carry out the analysis with other proxies for the size of the firm, e.g., sales and total assets. The qualitative implications of the results do not change when these proxies are used.

To test the predictive power of each grouping (information) variable, the median ROE of each portfolio is reported for the current and five subsequent years, denoted by ROE_0, $FROE_1$, ..., $FROE_5$. A good predictor is one that shows a large within-year variance of ROE and a stable pattern across years for each portfolio. The effect on ROE of a grouping variable is linear if there is a monotone linear relation over the five portfolio ROE for each year. We measure the statistical significance of the difference between the ROE of portfolio 1 and 5 for each year with the nonparametric two independent samples Mann-Whitney test.

Second, we carry out multivariate regression analyses. In particular we regress future ROE on the set of information variables and current ROE. This allows us to measure the predictive power of the included variables, incremental to current ROE. As in BR (1996), we focus on future ROE from one to five years into the future. The estimated regressions are (firm-indices are omitted):

$$FROE_t = a + bROE_0 + \sum_j c_j \cdot IV_{0,j} + e_t \tag{5}$$

where $FROE_t$= future ROE at time t, $t \in \{1, \ldots, 5\}$,

b = coefficient on current ROE_0,

c_j = coefficient on the jth current information variable $IV_{0,j}$,

e_t = error term.

The regression is run annually and we base our inferences on the time-series of coefficient estimates (see section 5.2).

4 Data and Sample.

The data are obtained from the Standard and Poor's Compustat CDROM of July 1997. The sample covers the period 1977-1996. The initial sample contains 14123 firms. When we define the industry variables concentration and market share, we use the largest sample possible, i.e., we use all observations for which we have non-negative sales. This criterion leads to a sample size of 101780 firm-years. Within this sample we define 76 sectors based on the SIC codes of the firms. We use an industry grouping scheme similar to but more elaborate than the scheme used by Biddle and Seow (1991). The scheme is also guided by the objective of obtaining a minimum

of 7 firms a year in each industry while attaining the highest possible intra-industry homogeneity. Appendix B provides an overview of the 76 sectors defined and shows how the observations are spread across the different industries. On an annual basis, the number of observations per industry varies between 7 and 616. The median (average) number of observations per industry is 44 (67).

We next impose a number of additional restrictions on the observations. In particular, in the samples we use for the prediction analyses, we require that book value is non-negative and that there are no missing values for earnings before extra-ordinary items, price (end of fiscal year-end and three months after year-end), and number of shares. In addition and consistent with previous studies on ROE prediction we delete the 2% of extreme observations (the 1st and 100th percentile) of the ROE and BTM distributions. After these restrictions, we retain a sample size of 37262 firm-year observations.

Table 1 and Table 2 provide some descriptive statistics for the samples. Table 1 shows that the distribution of a number of key variables is heavily skewed in the pooled sample. Also, both the mean and median of BTM are (significantly) lower than one, illustrating the presence of biased recognition in the measurement of book value. Table 2 reports the time series of medians and interquartile range of the same key variables. It appears that ROE decreases over the sample period and becomes more volatily. At the same time, BTM exhibits a declining time-trend. The median market value of the firms in the sample seems to decline at first but increases again during the last few years. The high interquartile range of market value relative to its median suggests that the sample contains a wide size-range of firms. The median returns exhibit a volatile pattern across the sample period.

5 Results.

The empirical findings are reported in two separate sections. A first section discusses the results from the univariate portfolio analyses and a second section presents the results of the multivariate analysis.

5.1 Univariate Portfolio Results.

This section presents the results of univariate tests of the association between the information variables of interest and ROE. Because current ROE is our benchmark information variable, we first illustrates how current ROE is associated with future ROE in Table 3. In other words, the results in Table 3 are obtained by using current ROE as our grouping variable. Based on the annual quintiles of current ROE, we form five portfolios in each year and compute the medians of current and future ROE within each portfolio. The results in the table clearly demonstrate the mean-reversing character of ROE, consistent with, among others, Penman (1991) and Bernard (1994). The Mann-Whitney test of median differences between portfolios 1 and 5 shows that the differences are highly significant for current ROE and for each of the future ROEs. The mean-reversion is illustrated by the decreasing MW-Z for years further into the future: the differences become less extreme but remain highly significant.

Fundamental signals.

Table 4 presents the results of the portfolio analysis based on the fundamental score $FSCORE$. As described in Appendix A, theoretically the possible values for $FSCORE$ range between 0 and 9. However, in our sample, all observations obtain the same value for the signals that measure auditor opinion and quality of earnings. We therefore include only the 7 other signals in the $FSCORE$ and obtain a initial range of $FSCORE$ between 0 and 7. Due to a lack of observations in the extreme portfolios with scores 0 or 7, we aggregate these observations into portfolio 1 and 6, respectively. We therefore obtain 6 portfolios in each year.

The results show that $FSCORE$ rank-orders firms on current profitability or ROE_0. The difference between the medians of portfolios 1 and 6 is highly significant based on the Mann-Whitney test. In addition, the results show that $FSCORE$ rank-orders firms on future profitability as well. Although the future ROE show a mean-reversing pattern, the difference between the medians of the two extreme portfolios remains significant.

In summary, it appears that the fundamental signals in the financial statements, aggregated into the $FSCORE$ exhibit explanatory power for current ROE and predictive power for future ROE up until five years into the future. This result extends the previous findings of LT (1993) and AB (1997) by illustrating a direct link between the fundamentals and current or future

ROE.

Accounting recognition.

Table 5 presents the results of the portfolio analyses based on *BTM* and its components *DR* and *BR*. Panel A shows that *BTM* rank-orders current *ROE*: a low *BTM* corresponds with a high *ROE*. This is not surprising, given that a low *BTM* implies large *UNA* and therefore a high *ROE*, as can be seen from valuation eq. (3). The difference between the medians of the two extreme portfolios is highly significant. *BTM* also rank-orders future profitability but the predictions exhibit a mean-reversing pattern: the *MW-Z* decreases from 29.650 to 13.184. The differences between the medians of the extreme portfolios remains significant though.

Panel B focuses on the explanatory and predictive power of the delayed recognition component of *BTM*. First, the results show that *DR* also positively rank-orders current *ROE* and the difference between the medians of the extreme portfolios is highly significant. In contrast, the results show that the predictive power for future *ROE* of *DR* is totally different from that of *BTM* in panel A. The first two years in the future *ROE* exhibit a strong mean-reversing pattern: *MW-Z* decreases from 29.377 to 6.405. However from year three in the future onwards, the pattern of future *ROE* *reverses*. Whereas a low *DR* corresponds with a high *ROE* in the current year and the first two years into the future, in years three through five into the future it seems to imply a low *ROE*. This result is slightly different from the one in BR (1996). BR show that future *ROE* demonstrates a strong mean-reversing pattern when ranked by *DR* but they do not observe a reversal of the future *ROE* pattern. We find the following explanation for this phenomenon. The firms in portfolio 1 (5) of the *DR* grouping in panel B obtain the highest (lowest) returns (this follows from the definition of *DR*), the highest (lowest) earnings-per-share and the lowest (highest) book values in the cross-section. Unreported analyses show that over the horizon in the future, book value increases gradually in all portfolios of panel B, so the reversal is due to the evolution of future earnings-per-share. We observe a strong increase in the earnings-per-share of portfolio 5 firms and a mild decline in earnings-per-share of portfolio 1 firms over the future horizon. This difference in the extent of change of earnings-per-share can be explained by the fact that portfolio 5 contains a large number of firms with a loss in the current year and previous literature has demonstrated that these losses are less persistent than profits. Therefore the reversal is caused by the relative difference in the rate of change in

earnings-per-share across the DR portfolios.

Panel C finally shows the results for the biased recognition portfolios based on BR. Again, BR rank-orders current ROE similar to BTM and DR. However, BR has different implications for the prediction of ROE. Future ROE does not exhibit a strong mean-reversing pattern in this particular case. In fact the MW-Z only slightly decreases over the five years into the future from 19.278 to 17.777.[19]

In summary, the results in Table 5 confirm the results of BR (1996) and demonstrate that the different components of BTM have different implications for the prediction of future ROE. BR measures a persistent difference between market and book value of the firm and therefore captures a persistent component of UNA of the firm. As a consequence, BR continues to rank-order future ROE in a manner similar to how it ranks current ROE. DR on the other hand measures temporary differences between market and book value of the firm and a temporary component of UNA. It therefore has less predictive power for future ROE than BR.

Industry characteristics.

Table 6 presents the results of the portfolio analysis based on the industry characteristics variables. This table differs from Tables 3-5 because the results are computed on an industry basis. To obtain the results we first compute median ROE per industry, hereafter industry ROE. Next we rank the *industries* based on the industry characteristics and compute annual portfolio medians of industry ROE. In other words, the table presents the pattern of median industry ROE and not median firm ROE.

In general the results for the industry variables are not strong. Panel A shows that industry concentration as measured by HHI rank-orders current industry ROE. The difference between the medians of the extreme portfolios is significant for a one-sided test but only marginally significant if we assume a two-sided test. However, the predictive power for future industry median ROE of HHI is limited. The pattern of future industry ROE across the five portfolios is clearly not always monotonic. Panel B shows that the results for the barriers-to-entry (as measured by $PPEAT$) is also weak. Barriers-to-entry as measured by the median capital intensity of the industry does not rank-order current industry ROE nor does it rank-order future industry

[19]Unreported analyses show that both median earnings-per-share and median book value per portfolio of panel C increase over the horizon in the future.

ROE. However, as pointed out in section 2.3, the SCP literature mainly discusses the effect of the *interaction* of concentration and barriers-to-entry on the profitability of industries. Panel C therefore provides the results of a portfolio analyses based on the interaction variable $INTIND$. The results show that this interaction variable rank-orders current median profitability of the industries. The difference between the medians of the extreme portfolios is significant for a one-sided test. Based on the *MW-Z*, the predictive power of this interaction variable for future industry median ROE seems to extend only two years into the future.

Table 7 illustrates the impact of market share on the profitability of the firm. As market share is computed per firm, this table again presents results based on firm ROE. The results are very strong. First, a high market share indicates a high current profitability. Second, market share also predicts profitability in the future: the rank-order of future ROE is maintained in each of the five years into the future. Similar to the BR results in Table 4, it seems that ROE does not exhibit a strong mean-reversion when ranked upon market share.

In summary, it appears that of the industry variables only market share gives strong results. As was discussed in section 2.3, this result is consistent with the recent IO literature. The interaction of concentration and barriers-to-entry seems to explain current industry profitability but has limited predictive power for future industry ROE. Assuming that the SCP paradigm is valid, one possible explanation for this weak result might be that we use inappropriate proxies for concentration or barriers-to-entry. However, sensitivity tests with other proxies (such as the $C4$ concentration index) provided similar results. Another explanation might be that ROE does not capture economic performance of the firm. The latter explanation is probably less likely because we see a clear relation between market share and ROE in Table 7. Still another plausible explanation might be that we do not capture adequately the notion of industry when we carry out our industry grouping based on SIC-codes.

We now focus our attention on the regression analyses.

5.2 Regression Results.

Table 8 contains the results of the regression analyses based on the annual estimation of eq. (5). The regressions are estimated using feasible generalized least squares (FGLS) assuming a heteroskedastic error variance matrix (White, 1980) . We use a maximum likelihood method

to obtain the firm-specific error variance $\hat{\sigma}_i^2$ estimates and the coefficients a, b and c_j. The advantage of doing the analysis on a year-by-year basis is twofold. First, we avoid estimating a more complex error variance matrix on the pooled dataset. Firm observations are serially correlated and additional time-series assumptions need to be made when the data are pooled over the whole sample period. Second, we do not restrict the coefficient estimates to be constant over time as in a pooled regression. Since we include current ROE in the regression equation, i.e. a lagged dependent variable, the error term is likely to be correlated with the independent variables. This causes coefficients a, b and c_j to be biased, especially in the equation that includes $FROE_1$ as a dependent variable, since ROE is highly serially correlated with $FROE_1$. We plan to examine the possible biases in our results in the future.[20]

Table 8 reports the mean coefficient and mean t statistic of the separate-year regressions. To test the coefficient estimate significance across all estimations, we compute two Z-statistics.[21] The $Z1$-statistic assumes residual independence which is unlikely to hold. We therefore also report a $Z2$-statistic that does not require this independence (see White 1984, and Barth et al. 1997).

Panel A of Table 8 reports the results of a benchmark regression where current ROE is the only independent variable. The results confirm that current ROE is a strong predictor of future ROE for each of the horizons considered. The Z-statistics are highly statistically significant for each equation. In addition, the pattern of results illustrates the mean-reversing nature of ROE, earlier demonstrated in Table 3: the magnitude of the mean coefficients and of the corresponding t and Z-statistics decreases as we predict ROE further into the future.

Panel B reports the results of the regressions of future ROE on current ROE, the information variables, and the two control variables. The results show that the fundamental signals or $FSCORE$ exhibit predictive power for future ROE incremental to current ROE and the other information variables up until four years into the future (based on the Z-statistics). The sign of the coefficient estimates of $FSCORE$ are consistently negative, indicating that lower values

[20] Greene (1993) mentions GMM estimation as a way to analyze models that include lagged dependent variables.

[21] The $Z1$-statistic is defined as $\frac{1}{\sqrt{T}}\sum_{j=1}^{T}\frac{t_j}{\sqrt{\frac{k_j}{k_j-2}}}$ where T is the number of years, t_j is the t statistic in year j, and k_j is the degrees of freedom per year (see Healy et al. 1987, and Barth et al. 1997). The $Z2$-statistic is defined as $\frac{\text{Mean } t_j}{\frac{\text{Std. Dev. } t_j}{\sqrt{T-1}}}$ (see White 1984, and Barth et al. 1997).

of $FSCORE$ reflect good news and predict an increase in future ROE. Finally, consistent with the mean-reversing pattern of future ROE demonstrated in Table 4, the coefficient magnitudes decrease as we move further into the future.

The patterns of coefficient estimates of the accounting recognition variables DR and BR demonstrate an important extension of the earlier presented univariate results in Table 5. First, DR provides incremental predictive power for future ROE in all regressions. The coefficient on DR in each case is significantly *positive*, illustrating the pattern reversal shown in panel B of table 5: a low DR corresponds with a high current ROE but it predicts a *low* future ROE. In addition, and again consistent with the results in panel B of Table 5, the coefficient magnitude of DR increases as we move further into the future. The earlier discussion regarding panel B of Table 5 suggests an explanation for this result. DR reflects transitory earnings that reverse in the future: an extreme DR means that current earnings contain a lot of transitory elements. The positive sign on DR follows from the fact that a low DR implies high earnings-per-share and vice versa. An important aspect of the results is that the information captured by DR is as important as or more important than the information in current ROE for the prediction of ROE from three years into the future onwards.

Second, consistent with the results in panel C of Table 5, BR is negatively related with future ROE. The coefficient of BR is statistically significant in each of the equations and becomes more negative as we move further into the future. This demonstrates the mean-reversion of ROE. However, the regression results also show that the BR coefficient is not significant in the first equation that predicts $FROE_1$. One explanation for this result is that in this multivariate context other variables in the equation are capturing the predictive power of BR for ROE in the near future. However, when the predictive power of these variables decreases as we move further into the future, BR gains in relative predictive power again because of its persistent relation with future ROE. This relation was illustrated in panel C of Table 5.[22]

The results for the industry characteristics variables in the regressions are largely consistent with the results in Tables 6 and 7. In contrast with the procedure followed to compute the results in Table 6 and to integrate HHI, $PPEAT$, and $INTIND$ into the regression analysis, we include these variables in the regressions on a firm-basis, rather than on an industry-basis. In

[22]One competing variable in the equation might be $PPEAT$ as it expresses capital intensity of the firm. BR (1996) discuss how capital intensity influences biased recognition. We plan to explore this issue further.

other words, in each of the separate-year estimations, firms in the same industry obtain the same value for these variables. As a reminder, MS is computed on a firm-basis. Generally speaking, the performance of the concentration and barriers-to-entry is weak relative to the other variables in the equation. HHI, $PPEAT$, and $INTIND$ provide no incremental predictive power for future ROE in most of the estimations. One exception is $PPEAT$ that exhibits predictive power for $FROE_1$ and $FROE_2$.[23]

MS exhibits statistically significant predictive power for future ROE, incremental to current ROE and the other information variables over the first three years of the horizon. This result is important for two reasons. First, it confirms more recent claims made in the IO literature suggesting that market share is a more important determinant of profitability than concentration or barriers-to-entry. Second, it also implies that information about the market share of the firm relevant for the future profitability of the firm is *not* fully captured by the other variables in the regression. We return to this point later.

We include $FINLEV$ and $SIZE$ in the equations to control for possible omitted variables. The results show that $FINLEV$ is negatively related to ROE, a result that is consistent with the Du Pont formula. Based on $Z2$, it appears that the coefficient on $FINLEV$ however is generally not statistically significant. In contrast, $SIZE$ is highly statistically significant in all regressions. The coefficient on $SIZE$ is positive, implying that larger firms will have higher future ROE. As $SIZE$ is often used as a proxy for financial health this result is consistent with the intuition that larger, healthier firms are predicted to be more profitable. Unreported analyses also suggest that $SIZE$ might be capturing part of the predictive power of MS. The analyses show that MS obtains a higher statistical significance in the first years of the horizon and that it remains significant over the full horizon in regressions that do not include $SIZE$. Earlier, we suggested that $SIZE$ might be a proxy for a number of industry characteristics such as economies-of-scale.

To summarize, the regression analysis shows that the three sets of information variables considered in this study contain variables that provide predictive power for future ROE incremental to current ROE. First, the aggregated fundamental signals, or $FSCORE$, predict future ROE up until four years into the future. Second, the accounting recognition variables

[23]The negative sign might be explained by the fact that capital intensive firms achieve low asset rotation. This influences return-on-assets and via the Du Pont formula ROE. We plan to explore this issue further.

also predict future ROE beyond current ROE. However, the two components of BTM that capture accounting recognition provide different information for future ROE. DR reflects transitory elements in earnings, is inversely related to earnings-per-share, and is therefore positively related to future ROE. BR on the other hand, is persistently and negatively related to future ROE. Third, market share or MS predicts future ROE in the presence of the other information variables and current ROE up until three years into the future. In contrast, concentration and barriers-to-entry provide no predictive power. In addition, it seems that $SIZE$, interpreted as a proxy for economies-of-scale captures some of the predictive power of MS.

6 Conclusion.

In this paper we study the predictive power for future ROE of three types of information variables: 1) fundamental signals summarized in a fundamental score of the firm; 2) accounting recognition variables defined as components of the BTM ratio of a firm; and 3) industry characteristics variables that measure concentration and barriers-to-entry in the industry and market share of the firm.

Our analyses lead to three findings. First, the fundamental score of the firm based on the financial statements contains information about the future profitability of the firm, not reflected in current profitability. This extends previous results presented by LT (1993) and AB (1997) who show that the fundamental signals both explain current returns and predict future earnings changes beyond current earnings changes.

Second, the accounting recognition variables identified by BR (1996) and based on the BTM predict future ROE in the presence of current ROE. However, the accounting recognition variables are associated differently with future ROE. Delayed recognition is positively associated with future ROE and biased recognition negatively. Additionally and somewhat surprisingly, delayed recognition has stronger predictive power for future ROE than biased recognition. An explanation is that the information in the biased recognition component of BTM is captured by other variables in the equation as well.

Third, the results for the industry characteristics variables are mixed. Our measures of concentration and barriers-to-entry provide little or no predictive power for future ROE. If

we believe that the SCP paradigm in the IO literature is valid, then one possible explanation for this weak result might be that we have misspecified the tests. In particular, although we define 76 industries based on SIC-codes, we may not have measured adequately the notion of the industry of the firms in the sample. Additionally, we may have used inappropriate proxies for concentration or barriers-to-entry. Finally, within the context of the IO profitability literature, ROE might not be an suitable proxy for profitability.

On the other hand, our analyses show that another IO variable, namely market share, is a strong predictor of future ROE. This is consistent with recent claims made in the IO literature that market share is a more important determinant of a firm's profitability than the concentration and barriers-to-entry of the industry in which it operates.

Overall, the conclusion of our analyses is that the three sets of variables have predictive power for future ROE incremental to current ROE and to each other. The implications for accountants are twofold. First, the evidence indicates that the accounting recognition variables are important predictors of the future ROE, in the presence of current ROE and the fundamental signals. This finding therefore confirms the conclusion by BR (1996) that it is important to consider the nature of GAAP recognition rules when carrying out fundamental analysis to predict future ROE. Accounting measures of profitability are driven both by the fundamentals and the GAAP recognition rules. Second, the fundamental signals capture information about future ROE not captured by current ROE or either other set of information variables. This implies that the information about future profitability comprised in certain line-items of the financial statements is broader than the information captured by summary measures such as ROE or the accounting recognition variables. This is somewhat surprising given that the accounting recognition variables refer to the information included in the market price. Future research can address the question why and under which circumstances this information is not reflected in the summary accounting variables.

Finally, the results show that the implications of current market share for the future profitability of the firm are *not* fully captured by current ROE, nor by the fundamental score, nor by the accounting recognition variables. This raises the question whether the market fully prices the importance of market share for future profitability.

Appendix A: Definition of Fundamental Signals

This appendix is based on Table 1 from AB (1997), Panel A. We consider 9 signals:

1. Inventory: Δ Inventory - Δ Sales.

2. Accounts Receivable: Δ Accounts Receivable - Δ Sales.

3. Capital Expenditures: Δ Industry Capital Expenditures - Δ Firm Capital Expenditures. Industry Capital expenditures are based on our industry definitions given in Appendix B.

4. Gross Margin: Δ Sales - Δ Gross Margin. Gross Margin is sales minus costs-of-goods-sold.

5. Selling and Administrative Expenses: Δ Selling and Administrative Expenses - Δ Sales.

6. Effective Tax Rate: $[(\frac{TR_{t-1}+TR_t}{2}) - TR_t] * CHEPS$. TR_t is the effective tax rate of the firm in year t. $CHEPS_t$ is the change in earnings per share of the firm over year t.

7. Earnings Quality: 0 for $LIFO$, 1 for $FIFO$ or other.

8. Audit Qualitifcation: 0 for unqualified, 1 for qualified or other.

9. Labor Force: $\frac{\frac{\text{Sales}_{t-1}}{\#Employees_{t-1}} - \frac{\text{Sales}_t}{\#Employees_t}}{\frac{\text{Sales}_{t-1}}{\#Employees_{t-1}}}$.

In all cases, the Δ operator represents a percentage change in the variable based on a two year average expectation model. As an example:

$$\Delta\text{Sales}_t = \frac{Sales_t - \frac{Sales_{t-1}+Sales_t}{2}}{\frac{Sales_{t-1}+Sales_t}{2}}$$

We refer the interested reader for more details to LT (1993) and AB (1997).

The signals are defined such that a negative value indicates good news, i.e. predicts a future earnings increase. For the sake of parsimony and consistent with LT and AB, we dichotimize the values of signals 1 through 6, and signal 9. A negative (positive) value is assigned a value of zero (one). Finally, our aggregate fundamental score, $FSCORE$, is then computed as the sum of the assigned values. The interpretation is that a low value of $FSCORE$ indicates good news for future profitability.

Appendix B: Industry Definition

The following table lists our definition of industries and the number of observations within each industry (over the complete sample period).

	Industry Name	Obs.
1	mining	832
2	oil and gas exploration	1783
3	construction	698
4	food and tobacco	1056
5	textiles	458
6	apparel	478
7	lumber and wood products	354
8	furniture and fixtures	416
9	paper and allied products	448
10	publish	366
11	commercial printing, typesetting	403
12	chemicals and allied products	275
13	pharmaceuticals	1577
14	special chemicals: soap, polish, paint, etc.	766
15	petroleum refining	123
16	rubber, plastic and leather products	794
17	glass	54
18	cement, ceramics, pottery, asbestos	257
19	metal industry: steel, iron foundries	398
20	nonferro metals	216
21	structural metal, hardware, steel stamping	1137
22	engines, turbines, machinery, tractors	586
23	special industry machinery	1154
24	computer, related devices and office machines	1307
25	refrigerators, laundry machines, pumps	399
26	motors and generators	400
27	household equipment	385
28	electric lighting	308
29	audio, video	131

	Industry Name	Obs.
30	communication apparatus (telephone)	1236
31	semiconductor, printed circuit board	1564
32	automobile	489
33	aircraft, missiles and parts	171
34	ship building	213
35	measurement instruments	1600
36	surgical, medical and dental instruments	1400
37	photographic equipment	104
38	miscalleneous manufacturing	390
39	toys and games	135
40	sport, athletic goods	169
41	transportation (trucking,bus,air)	661
42	airlines	120
43	telephone and telegraph	402
44	radio, TV stations, cable	227
45	utilities	1872
46	motor vehicle parts, tires	92
47	computer and software wholesale	274
48	wholesale metal, minerals	82
49	electrical apparatus	379
50	hardware wholesale	122
51	machinery and equipment wholesale	213
52	miscellaneous wholesale	236
53	drugs and proprietary wholesale	100
54	apparel, miscellaneous nondurables wholesale	119
55	groceries wholesale	150
56	chemicals, plastics wholesale	243
57	lumber, furniture, building metal wholesale	185
58	department stores	270
59	food stores, groceries	247
60	auto dealers, gas stations	150
61	apparel, clothing	382

	Industry Name	Obs.
62	home furniture	139
63	radio, TV, computer, software	127
64	restaurants, drinking	816
65	miscellaneous retail	463
66	mail order	153
67	hotels	200
68	personal services	147
69	advertising	159
70	rental and leasing	150
71	employment agencies	215
72	computer programming, software	1764
73	miscellaneous business services	517
74	auto rental, lease and repair	114
75	motion pictures, theatres	308
76	amusement and recreation services	434
	total :	37262

The data are collected from *PC Plus Compustat* (July 1997) and are pooled over 1977-1996. Outliers have been deleted as indicated in the text.

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TABLE 1

Descriptive Statistics: Pooled Sample[a]

	# Obs.	Mean	Std. Dev.	Q1	Median	Q3
ROE	37262	0.029	0.325	-0.027	0.098	0.183
BTM	37262	0.745	0.562	0.354	0.606	0.975
Market Value	37262	148.797	306.294	15.194	50.379	154.830
RET	37262	0.161	0.624	-0.222	0.043	0.379

[a] The data are collected from *PC Plus Compustat* (July 1997) and are pooled over 1977-1996. *ROE* is defined as income before extra-ordinary items divided by beginning-of-year book value. *BTM* is book value of equity divided by market value of equity. Market value of equity is the market value of outstanding equity three months following fiscal year-end in millions of U.S. dollars. *RET* is security return over the fiscal year. Outliers have been deleted as indicated in the text.

TABLE 2

Descriptive Statistics: Annual Samples[a]

		ROE		*BTM*		*Market Value*		*RET*	
	# Obs.	Med.	IQR	Med.	IQR	Med.	IQR	Med.	IQR
1978	844	0.170	0.112	1.031	0.728	41.295	103.282	0.106	0.449
1979	1020	0.183	0.123	0.938	0.831	41.771	109.881	0.141	0.566
1980	1096	0.162	0.141	0.840	0.878	45.812	118.770	0.223	0.676
1981	1157	0.153	0.140	0.826	0.832	40.874	103.667	0.000	0.499
1982	1310	0.121	0.146	0.738	0.775	40.144	110.256	0.153	0.664
1983	1338	0.130	0.168	0.589	0.549	55.809	139.889	0.276	0.690
1984	1514	0.129	0.163	0.660	0.550	45.513	119.308	-0.089	0.445
1985	1609	0.101	0.178	0.607	0.501	47.240	126.885	0.147	0.580
1986	1682	0.088	0.193	0.597	0.468	48.566	132.003	0.067	0.562
1987	1833	0.090	0.192	0.656	0.570	39.900	110.345	-0.092	0.499
1988	2003	0.100	0.215	0.648	0.547	37.625	112.254	0.040	0.518
1989	2093	0.087	0.217	0.631	0.597	39.480	117.840	0.021	0.556
1990	2181	0.069	0.215	0.783	0.802	30.837	98.351	-0.180	0.493
1991	2292	0.059	0.227	0.630	0.732	43.089	132.018	0.182	0.762
1992	2406	0.070	0.221	0.571	0.603	54.473	150.920	0.057	0.611
1993	2684	0.073	0.244	0.492	0.492	64.104	175.654	0.106	0.660
1994	3106	0.083	0.258	0.545	0.535	60.036	155.813	-0.100	0.514
1995	3440	0.079	0.285	0.481	0.512	70.905	189.213	0.109	0.730
1996	3654	0.078	0.300	0.480	0.498	73.637	200.650	0.031	0.650

[a] The data are collected from *PC Plus Compustat* (July 1997) and are pooled over 1977-1996. *ROE* is defined as income before extra-ordinary items divided by beginning-of-year book value. *BTM* is book value of equity divided by market value of equity. Market value of equity is the market value of outstanding equity three months following fiscal year-end in millions of U.S. dollars. *RET* is security return over the fiscal year. Outliers have been deleted as indicated in the text. *Med* is the median of the sample, *IQR* is the interquartile range of the sample.

TABLE 3

ROE Mean Reversion [a]

	Portf.[b]	# Obs.	ROE_0	$FROE_1$	$FROE_2$	$FROE_3$	$FROE_4$	$FROE_5$
Low	1	3175	-0.095	-0.006	0.022	0.040	0.046	0.050
	2	3178	0.052	0.062	0.069	0.072	0.077	0.081
	3	3182	0.117	0.116	0.113	0.113	0.110	0.110
	4	3178	0.173	0.156	0.140	0.131	0.124	0.122
High	5	3186	0.277	0.227	0.182	0.156	0.140	0.133
MW-Z[c]*: Portf. 1-5*			-69.065	-53.613	-39.646	-29.670	-24.240	-21.133

[a] The data are collected from *PC Plus Compustat* (July 1997) and are pooled over 1977-1996. Outliers have been deleted as indicated in the text. The table presents the *medians* of the *ROE* distribution in each portfolio where *ROE* is defined as income before extra-ordinary items divided by beginning-of-year book value. ROE_0 is current *ROE* in the year in which the portfolio was formed, and $FROE_t$ is *ROE* t years in the future after portfolio formation.

[b] The portfolios are based on the quintiles of the annual distribution of *ROE*.

[c] MW-Z is based on the Normal Approximation of the Mann-Whitney two sample test. The *null* hypothesis states that the medians of the *ROE* portfolios 1 and 5 is the same.

TABLE 4

Fundamental Score and ROE[a]

	Portf.[b]	# Obs.	ROE_0	$FROE_1$	$FROE_2$	$FROE_3$	$FROE_4$	$FROE_5$
Low	1	969	0.151	0.138	0.125	0.112	0.108	0.100
	2	1827	0.132	0.122	0.109	0.104	0.106	0.103
	3	2332	0.120	0.114	0.105	0.103	0.100	0.098
	4	2080	0.101	0.098	0.094	0.097	0.094	0.087
	5	1279	0.079	0.082	0.087	0.088	0.088	0.092
High	6	584	0.045	0.058	0.069	0.072	0.076	0.077
MW-Z[c]: Portf. 1-6			-16.514	-12.909	-8.971	-6.685	-5.638	-3.988

[a] The data are collected from *PC Plus Compustat* (July 1997) and are pooled over 1977-1996. Outliers have been deleted as indicated in the text. The table presents the *medians* of the *ROE* distribution in each portfolio where *ROE* is defined as income before extra-ordinary items divided by beginning-of-year book value. ROE_0 is current *ROE* in the year in which the portfolio was formed, and $FROE_t$ is *ROE* t years in the future after portfolio formation.

[b] The portfolios are based on the fundamental score *FSCORE*, obtained from aggregating the dichotomized individual fundamental signals as described in the text and appendix A. A low *FSCORE* indicates good news.

[c] MW-Z is based on the Normal Approximation of the Mann-Whitney two sample test. The *null* hypothesis states that the medians of the *ROE* portfolios 0 and 6 is the same.

TABLE 5

Accounting Recognition and ROE[a]

Panel A: *BTM* Portfolios

	Portf.[b]	# Obs.	ROE_0	$FROE_1$	$FROE_2$	$FROE_3$	$FROE_4$	$FROE_5$
Low	1	1309	0.200	0.190	0.169	0.156	0.145	0.135
	2	1312	0.145	0.133	0.124	0.118	0.114	0.113
	3	1313	0.117	0.109	0.104	0.106	0.108	0.109
	4	1312	0.088	0.085	0.083	0.087	0.092	0.095
High	5	1317	0.031	0.032	0.046	0.055	0.065	0.066
MW-Z[e]: Portf. 1-5			29.650	28.709	22.529	17.607	14.602	13.184

Panel B: *DR* Portfolios

	Portf.[c]	# Obs.	ROE_0	$FROE_1$	$FROE_2$	$FROE_3$	$FROE_4$	$FROE_5$
Low	1	1309	0.172	0.147	0.116	0.097	0.088	0.086
	2	1312	0.139	0.124	0.110	0.106	0.098	0.102
	3	1313	0.111	0.109	0.105	0.103	0.105	0.105
	4	1312	0.083	0.087	0.089	0.096	0.104	0.106
High	5	1317	0.031	0.056	0.081	0.099	0.118	0.125
MW-Z[e]: Portf. 1-5			29.377	17.101	6.405	-2.252	-7.684	-9.111

Panel C: *BR* Portfolios

	Portf.[d]	# Obs.	ROE_0	$FROE_1$	$FROE_2$	$FROE_3$	$FROE_4$	$FROE_5$
Low	1	1309	0.158	0.153	0.146	0.145	0.144	0.143
	2	1312	0.134	0.131	0.129	0.128	0.125	0.125
	3	1313	0.121	0.117	0.112	0.114	0.116	0.115
	4	1312	0.093	0.088	0.084	0.085	0.084	0.088
High	5	1317	0.055	0.048	0.042	0.043	0.043	0.044
MW-Z[e]: Portf. 1-5			19.278	19.420	18.675	17.880	18.034	17.777

[a] The data are collected from *PC Plus Compustat* (July 1997) and are pooled over 1977-1996. Outliers have been deleted as indicated in the text. The table presents the *medians* of the *ROE* distribution in each portfolio where *ROE* is defined as income before extra-ordinary items divided by beginning-of-year book value. ROE_0 is current *ROE* in the year in which the portfolio was formed, and $FROE_t$ is *ROE* t years in the future after portfolio formation.

[b] The portfolios are based on the quintiles of the annual distribution of *BTM*, defined as book value of equity divided by market value of equity.

[c] The portfolios are based on the quintiles of the annual distribution of *DR*, the delayed recognition component of *BTM*. As described in the text, *DR* is computed following the methodology of Beaver and Ryan (1996).

[d] The portfolios are based on the quintiles of the annual distribution of *BR*, the biased recognition component of *BTM*. As described in the text, *BR* is computed following the methodology of Beaver and Ryan (1996).

[e] MW-Z is based on the Normal Approximation of the Mann-Whitney two sample test. The *null* hypothesis states that the medians of the *ROE* portfolios 1 and 5 is the same.

TABLE 6

Industry Variables and Industry Median ROE[a]

Panel A: Concentration Portfolios

	Portf.[b]	# Obs.	ROE_0	$FROE_1$	$FROE_2$	$FROE_3$	$FROE_4$	$FROE_5$
Low	1	158	0.124	0.118	0.112	0.108	0.107	0.103
	2	161	0.124	0.114	0.114	0.105	0.100	0.101
	3	165	0.129	0.120	0.108	0.102	0.109	0.110
	4	161	0.135	0.118	0.113	0.110	0.107	0.097
High	5	169	0.141	0.129	0.126	0.118	0.107	0.103
MW-Z[e]: Portf. 1-5			-1.992	-2.736	-2.508	-1.466	-0.532	-0.159

Panel B: Barriers-to-Entry Portfolios

	Portf.[c]	# Obs.	ROE_0	$FROE_1$	$FROE_2$	$FROE_3$	$FROE_4$	$FROE_5$
Low	1	158	0.125	0.119	0.114	0.111	0.104	0.105
	2	161	0.122	0.107	0.098	0.098	0.095	0.092
	3	165	0.131	0.126	0.111	0.111	0.107	0.108
	4	161	0.136	0.127	0.116	0.108	0.111	0.110
High	5	169	0.135	0.121	0.119	0.113	0.112	0.111
MW-Z[e]: Portf. 1-5			-0.208	0.448	-0.006	-0.230	-0.141	-0.292

Panel C: Concentration/Barriers-to-Entry Portfolios

	Portf.[d]	# Obs.	ROE_0	$FROE_1$	$FROE_2$	$FROE_3$	$FROE_4$	$FROE_5$
Low	1	158	0.119	0.114	0.110	0.102	0.102	0.102
	2	161	0.127	0.116	0.108	0.111	0.111	0.105
	3	165	0.130	0.117	0.117	0.103	0.106	0.101
	4	161	0.138	0.127	0.116	0.112	0.107	0.102
High	5	169	0.139	0.126	0.118	0.113	0.108	0.106
MW-Z[e]: Portf. 1-5			-1.947	-2.189	-2.288	-1.532	-1.054	-0.507

[a] The data are collected from *PC Plus Compustat* (July 1997) and are pooled over 1977-1996. Outliers have been deleted as indicated in the text. The table presents the *medians* of the Industry ROE distribution in each portfolio where ROE is defined as income before extra-ordinary items divided by beginning-of-year book value. ROE_0 is current ROE in the year in which the portfolio was formed, and $FROE_t$ is ROE t years in the future after portfolio formation.

[b] The portfolios are based on the quintiles of the annual distribution of HHI, the industry concentration index based on sales of the firms in the industry.

[c] The portfolios are based on the quintiles of the annual distribution of $PPEAT$, the measure of capital intensity, defined as property, plant, and equipment divided by total assets.

[d] The portfolios are based on the quintiles of the annual distribution of $INTIND$ or the product of HHI and $PPEAT$. This variable measures the interaction between concentration and barriers-to-entry in the industry.

[e] MW-Z is based on the Normal Approximation of the Mann-Whitney two sample test. The *null* hypothesis states that the medians of the ROE portfolios 1 and 5 is the same.

TABLE 7

Market Share and ROE[a]

	Portf.[b]	# Obs.	ROE_0	$FROE_1$	$FROE_2$	$FROE_3$	$FROE_4$	$FROE_5$
Low	1	3175	0.064	0.070	0.068	0.064	0.061	0.060
	2	3178	0.113	0.106	0.099	0.095	0.093	0.091
	3	3182	0.131	0.123	0.118	0.113	0.110	0.108
	4	3178	0.139	0.128	0.118	0.117	0.114	0.115
High	5	3186	0.148	0.135	0.126	0.121	0.120	0.120
MW-Z[c]: Portf. 1-5			-24.254	-19.370	-17.417	-17.071	-18.155	-18.532

[a] The data are collected from *PC Plus Compustat* (July 1997) and are pooled over 1977-1996. Outliers have been deleted as indicated in the text. The table presents the *medians* of the ROE distribution in each portfolio where ROE is defined as income before extra-ordinary items divided by beginning-of-year book value. ROE_0 is current ROE in the year in which the portfolio was formed, and $FROE_t$ is ROE t years in the future after portfolio formation.

[b] The portfolios are based on the quintiles of the annual distribution of MS, defined as the sales of the company divided by the sum of the sales within the industry.

[c] MW-Z is based on the Normal Approximation of the Mann-Whitney two sample test. The *null* hypothesis states that the medians of the ROE portfolios 1 and 5 is the same.

TABLE 8

Regression Results[a]

Panel A: *ROE* Benchmark Results

Dep. Var.	Indep. Var.	Mean Coef.	Mean t stat.	$Z1$	$Z2$
$FROE_1$	*ROE*	0.583	9.243	36.934	21.143
$FROE_2$	*ROE*	0.399	6.556	25.363	20.319
$FROE_3$	*ROE*	0.290	4.390	16.409	12.704
$FROE_4$	*ROE*	0.229	3.596	12.949	15.198
$FROE_5$	*ROE*	0.160	2.689	9.303	7.355

Panel B: *ROE*, Information Variables and Controls

Dep. Var.	Indep. Var.	Mean Coef.	Mean t stat.	$Z1$	$Z2$
$FROE_1$	*ROE*	0.488	5.543	19.960	14.436
	FSCORE	-0.009	-2.060	-7.417	-6.801
	DR	0.027	0.716	2.580	2.216
	BR	-0.008	-0.455	-1.638	-0.992
	HHI	-0.002	0.114	0.411	0.338
	PPEAT	-0.070	-0.881	-3.173	-2.789
	INTIND	0.204	0.327	1.176	0.933
	MS	-0.001	-0.590	-2.126	-2.025
	FINLEV	-0.026	-0.673	-2.425	-1.479
	SIZE	0.016	2.398	8.633	5.448
$FROE_2$	*ROE*	0.367	4.595	15.894	13.414
	FSCORE	-0.008	-1.626	-5.624	-4.563
	DR	0.133	2.810	9.720	9.841
	BR	-0.017	-0.847	-2.927	-1.356
	HHI	0.023	0.140	0.484	0.398
	PPEAT	-0.073	-0.734	-2.537	-2.345
	INTIND	0.293	0.307	1.060	0.841
	MS	-0.002	-0.642	-2.221	-2.137
	FINLEV	-0.025	-0.633	-2.192	-1.476
	SIZE	0.018	2.297	7.947	5.174

TABLE 8

Regression Results (continued)[a]

Dep. Var.	Indep. Var.	Mean Coef.	Mean t stat.	$Z1$	$Z2$
$FROE_3$	ROE	0.337	4.151	13.745	16.003
	$FSCORE$	-0.007	-1.206	-3.994	-4.874
	DR	0.197	4.156	13.762	15.212
	BR	-0.026	-1.088	-3.601	-1.993
	HHI	0.099	0.299	0.989	0.887
	$PPEAT$	-0.051	-0.491	-1.624	-1.435
	$INTIND$	-0.170	0.072	0.238	0.199
	MS	-0.001	-0.550	-1.821	-1.912
	$FINLEV$	-0.030	-0.708	-2.346	-1.781
	$SIZE$	0.016	1.874	6.207	3.659
$FROE_4$	ROE	0.295	3.721	11.747	17.550
	$FSCORE$	-0.006	-1.195	-3.771	-3.001
	DR	0.239	4.832	15.255	14.940
	BR	-0.035	-1.268	-4.002	-2.418
	HHI	0.087	0.381	1.203	0.909
	$PPEAT$	-0.040	-0.323	-1.019	-0.850
	$INTIND$	-0.048	-0.102	-0.322	-0.269
	MS	-0.001	-0.274	-0.866	-0.714
	$FINLEV$	-0.029	-0.668	-2.110	-1.411
	$SIZE$	0.016	1.797	5.675	3.294
$FROE_5$	ROE	0.229	2.700	8.085	8.857
	$FSCORE$	-0.002	-0.248	-0.743	-0.538
	DR	0.227	4.568	13.680	16.062
	BR	-0.045	-1.548	-4.636	-3.352
	HHI	0.066	0.245	0.735	0.653
	$PPEAT$	-0.056	-0.358	-1.071	-0.742
	$INTIND$	-0.143	-0.034	-0.105	-0.08
	MS	-0.001	-0.307	-0.919	-0.889
	$FINLEV$	-0.025	-0.502	-1.504	-1.617
	$SIZE$	0.016	1.719	5.148	3.253

[a] The data are collected from *PC Plus Compustat* (July 1997) and are pooled over 1977-1996. Outliers have been deleted as indicated in the text. The regression estimated is of the following general form:

$$FROE_t = a + bROE_0 + \sum_j c_j \cdot IV_{0,j} + e_t$$

where $FROE_t$ is future ROE at time t, $t \in \{1, \ldots, 5\}$, b is the coefficient on current ROE_0, c_j is the coefficient on the jth current information variable $IV_{0,j}$, and e_t is the error term.

This equation is estimated annually and the table reports the means of the time-series of coefficients and corresponding t statistics. We base our inferences on three Z-statistics also reported in the table. The $Z1$-statistic is defined as $\frac{1}{\sqrt{T}} \sum_{j=1}^{T} \frac{t_j}{\sqrt{\frac{k_j}{k_j-2}}}$ where T is the number of years, t_j is the t statistic in year j, and k_j is the degrees of freedom per year (see Healy et al. 1987, and Barth et al. 1997). The $Z2$-statistic is defined as $\frac{\text{Mean } t_j}{\text{Std. Dev. } t_j \sqrt{T-1}}$ (see White 1984 and Barth et al. 1997).

The IV included in the regression equation in the different panels of the table are defined as indicated in the text and previous tables.

The average number of observations in the regressions of Panel A is 1066, 975, 901, 832, and 768, respectively. The average number of observations in the regressions of Panel B is 739, 708, 674, 633, and 583, respectively.