Is stock price a good measure for assessing value-relevance of earnings?

An empirical test

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ABSTRACT

Recently, a growing body of literature has created a widespread impression that financial statements have lost their value-relevance because of a shift from traditional capital-intensive economy into a high technology, service-oriented economy. In particular, the claim is that financial statements are less relevant in assessing the fundamental value of high technology, service-oriented firms/activities, which are by nature knowledge-intensive. These conclusions are based on past studies that examine the association between accounting numbers (i.e., earnings and book values) and stock prices and show that, in general, the association between accounting information and stock prices has been declining, over time. These findings have been interpreted to be the result of a decline in value relevance of accounting. We examine the predictive content of stock prices and accounting information, as against the contemporaneous association between accounting information and stock prices. We find that while both the predictive content of earnings and prices declined over time, the predictive content of price signals declined by even more. Our analysis suggest that the declining association could be the consequence of increased noise in stock prices over time resulting from increases in trading volume driven by non-information based trades, and not just a decline in the predictive content of earnings. More importantly, this conclusion is consistent with the insights of the noisy rational expectations equilibrium framework analysis, i.e. that increased noise has caused the predictive content of prices to degrade over time. Overall, our evidence suggests that stock prices may not be an appropriate benchmark for gauging the information content of accounting earnings.

I. Introduction

Recently, a growing body of literature has created a widespread impression that financial statements have lost their value-relevance because of a shift from traditional capital-intensive economy into a high technology, service-oriented economy. In particular, the claim is that financial statements are less relevant in assessing the fundamental value of high technology, service-oriented firms/activities, which are by nature knowledge-intensive (for example see "Jenkins Committee" report of the AICPA special committee on financial reporting; Elliott and Jacobsen, 1991, Jenkins, 1994, Reimerman, 1990, and Sever and Boisclaire, 1990). Ramesh and Thiagarajan (1995), Lev, (1997), Chang (1998), Lev and Zarowin (1999), Francis and Schipper (1999) and Brown et al. (1999) document a decline in the value-relevance of earnings over time. These studies examine the association between a combination of earnings, change in earnings and book value and contemporaneous stock price or returns. The authors of these studies generally view the R^2s or coefficients on the explanatory variables in these regressions as a reflection of value-relevance. An exception to these findings is provided by Collins et. al. (1997) who show that when book values are added as independent variables along with earnings, the value-relevance holds steady or improves over time. Specifically, they find that the incremental value-relevance of earnings (book value) declines (increases) in the frequency of non-recurring items and of negative earnings. These findings prompt the authors to suggest that claims that the conventional historical cost accounting model has lost its value relevance are premature. Brown et al. (1998), however, argue that a scale factor common to price per share, EPS, and book value per share induces a spurious increase in value-relevance over time. After controlling for the scale, they find that incremental value-relevance of both earnings and book value, in fact, has declined over time. These studies use price as a benchmark, assuming it reflects the fundamental value of the security with less noise than alternative measures. A further assumption implicit in these studies is that the process by which the contemporaneous stock price reflects value-relevant information (both accounting and non-accounting) remains unchanged over time.

This paper investigates the validity of these assumptions, i.e., prices reflect fundamental values with less noise than accounting information. We have reason to believe that price may not be the "best" reflection of fundamental value[1]. If trading activity is partly due to non-information-based (NIB) trading (global and inter-sectoral wealth transfers, etc.), then stock prices could be noisy. We use a Noisy Rational Expectations Equilibrium (NREE) framework to show that an increase in NIB trading makes prices less informative about future payoffs (Kim and Verrecchia (1991) and Dontoh and Ronen (1993)).[2]. Accounting information on the other hand, while noisy, is independent of such NIB trading behavior. Consequently, if NIB trading has given rise to decreased information content (increased noisiness) of stock prices with respect to future payoffs, the contemporaneous association of stock prices and earnings would decrease, not because of the decreased quality of earnings but because of the increased noise in stock prices. In this case, prices may not be the proper benchmark to assess the value relevance of earnings, at a given point in time, or over time.[3]

We investigate this analytical insight by focusing our empirical examination on the information content of earnings vis à vis the information content of prices, and not on the contemporaneous association between earnings and stock prices ("value-relevance" as has been defined in earlier empirical studies.) Consistent with the NREE model, we define the information content of earnings or prices as the degree to which these measures (earnings

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[1] In addition, recent studies on market volatility, liquidity, transaction costs and trading volume suggest that the stock price formation process has changed over time (see, for example, Greene and Smart, 1994; Odean, 1999; Finnerty and Gu, 2000; and Stevens and Oconnoly, 2000). Specifically, evidence in these studies suggests that trading activity in recent years has increased in a way that affects the stock price formation process.

[2] Grossman (1995) characterized non-information based trading as follows: "in general, there may be many reasons for trade other than information. After all, the traditional view of the market is of a location where resources are reallocated. Reasons for these non-informational trades include cross-sectional changes in wealth, risk-preferences, liquidity needs, unanticipated investment opportunities and all other factors that do not directly relate to the payoffs of traded securities." For instance, in response to random shocks in their wealth or preferences, traders may re-optimize their global portfolios including non-financial assets. The results of such reoptimizations, when restricted to a single market such as the stock market, may appear as random perturbations in asset-holdings that are unrelated to information about underlying market values. A similar notion is embedded in the concept of market created risk succinctly stated by Krause and Smith (1989, p. 558): "however, uncertainty about future prices can also reflect uncertainty about what we call the 'state of the market': the beliefs, preferences and endowments of the other participants in the economy. Even if all investors' probability beliefs about ultimate payoffs were common knowledge, as well as the knowledge that these beliefs would not change in the future, uncertainty about future prices would still be present as long as investors had imperfect information about the state of the market. We refer to this source of uncertainty as "market created risk" to emphasize that its source is investors themselves, rather than the stochastic process describing the ultimate cash payouts to securities."

[3] We provide evidence that non-information based (NIB) trading could have increased the noise in stock prices. This is consistent with the noisy-rational-expectations-equilibrium (NREE) model, which we use to provide analytical insights.

or prices) reflect the fundamental value of the firm. We adopt two perspectives for operationalizing the concept of "fundamental value." One is the vector of the present values of future realized flows (dividends or earnings[4]) and a terminal value, and the other is the undiscounted vector of these flows (more on this later). It is important to emphasize that our proxy for the fundamental value is future earnings or cash flows – information not available at time *t* when investors form their subjective valuations of the firm. As such, we use hindsight information not available to investors in real time to ascertain, from a researcher's perspective, the viability of the stock price as a proxy for fundamental value to be potentially used to assess the value relevance of earnings. Hence, we are <u>not</u> interested in a valuation exercise that utilizes only comtemporaneously available information such as reported earnings (and components thereof), book value (and components thereof) or analysts' forecasts.

To test the relative information content as measured by the predictive content of current earnings and stock prices, we regress, separately, current period earnings and stock prices on the future periods' earnings or dividends flows. In both regressions, we use the same set of independent variables: future periods' earnings or dividends flows and proxy for the remaining infinite sequence of flows with a terminal value. As a proxy for the terminal value component of the fundamental value, we use the price of the stock at a future date[5]. We compare the R^2 (considered as the measure of information content) of the annual price and earnings regressions.[6] We find that the R^2 of the earnings regression is, in general, significantly higher than the R^2 of the price regression.[7] While the R^2 of the earnings regression declines over time, the R^2 of the price regression declines even more. In other words, the ratio of the earnings regression R^2 to the price regression R^2 increases over time. This evidence suggests that the information content of earnings relative to the information content of stock prices has increased over time. This is consistent with our analysis of the increases in NIB trading within NREE framework we discussed earlier. The

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[4] From here on, earnings and net income will be used interchangeably.
[5] A number of studies have assessed the performance of valuation models; for example see Penman and Sougiannis (1998), Lee et. al. (1999a), Lee (1999b), Liu and Thomas (2000) and Francis et. al. (2000). Our motivation here is to test the relative information content as measured by the predictive content of current earnings versus stock prices and not to test any particular valuation model.
[6] We derive rigorously in Appendix A, the monotone relation between R^2 and information content .
[7] We develop a statistical test (yielding a G statistic) for comparing the equality of R^2 across the two regressions. The G-statistic test is derived in Appendix B.

information content of earnings is independent of investors' beliefs and perceptions and other non-information related forces, while stock prices are jointly determined by the firm's fundamentals and investors' beliefs and perceptions, as well as liquidity needs and capital movements. The effect of investors' beliefs and perceptions on the information content of stock prices and trading volume activity has been demonstrated by other studies using different frameworks for analyses (for example, see Odean, 1998; Shefrin and Statman, 1994; Benos, 1998, Kyle and Wang, 1997, and Daniel, Hirshleifer and Subrahmanyam, 1998). In general, these models show that when investors are overconfident or biased stock prices would be distorted, i.e., be less informative and would be associated with increased trading activity. Our empirical finding indicates that the information content of stock prices has decreased overtime in addition to being mostly below that of earnings, which suggests that the factors contributing to noise in prices have become more manifest overtime.

The R^2 of the earnings regression is statistically significantly higher than the R^2 of the price regressions, even after controlling for size, book-to-market ratios and intangible-intensity (as in Collins et. al., 1997). We find that the decline in the information content of stock prices over time is more pronounced for small-sized firms than for large-sized firms. Specifically, the ratio of the earnings regression R^2 to the stock price regression R^2 is almost flat for the large size firms, while for the small-sized firms the ratio has increased considerably. Similarly, the ratio of the earnings regression R^2 to the stock price regression R^2 is almost flat for the low book-to-market ratio (high growth), while for the high book-to-market ratio (low growth) the ratio has risen.

We then investigate whether non-information based trading possibly has led to the decline in information content of stock prices over time. We use the annual cross-sectional mean trading volume as a measure of the level of non-information based trading.[8] We find that the annual cross-sectional mean trading volume is highly negatively correlated with the R^2 of the price regression, confirming our conjecture (based on the NREE model) that the decline in the information content of stock prices is driven by an increase in non-

[8] Dontoh and Ronen (1993) and Kim and Verecchia (1991) show that trading volume increases in non-information based trading. Chiang and Venkatesh (1988) show that trading volume is highly negatively correlated with bid-ask spreads. A higher bid-ask spread is associated with informational-difference-related

information based trading. We control for the annual mean loss, annual mean one-time items and the annual mean intangible intensity, which are factors that were shown to be associated with the explanatory power of earnings (see Collins et. al., 1997), and find that these variables do not explain the decline in the information content of prices.

Our evidence has important implication for the research design of value relevance studies, which base inferences on the strength of the association between stock prices and accounting numbers. Specifically, our results show that to draw conclusions about the information content of earnings at a point in time or over time, we need to control for market factors that influence the formation of stock prices. An indirect policy implication is that accounting numbers may not have lost information content. More importantly, we should react cautiously to evidence on the declining association of earnings and stock prices over time.

Our evidence also provides indirect support for the theoretical studies that explore investor overconfidence and biases. Our findings suggest that factors such as these have become more manifest overtime leading to higher NIB trading and noise in the stock price. While we do not provide evidence on why investor bias and such other factors may have become more evident overtime, our study implies that noise in publicly disseminated accounting data might not be the reason. Our evidence also supports the conjecture that stock prices could have become noisier due to NIB trading (among various other factors).

II. Development of the research design

In Appendix A, we derive insights into the relative information content of earnings and prices when the non-information based (NIB) trading increases by analyzing a Noisy Rational Expectations Equilibrium (NREE). The analysis provides the following result.[9]

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transaction cost (see Glosten and Milgrom, 1985). Conversely, when the specialist (market maker) faces less informed traders, the bid ask spread would decrease.

[9] The analysis is non-trivial and it furnishes insights into the informativeness of stock prices when both NIB trading increases and the informativeness of earnings decreases. It was also necessary to develop definitions of the informativeness of earnings and prices that build on Dontoh and Ronen (1993) and Kim and Verecchia (1991). While these are important analytical contributions, for purposes of brevity we relegate the analysis to the Appendix.

Result on relative informativeness of earnings and prices

An increase in trading volume and a decrease in the predictive content of earnings will be associated with a decrease in the predictive content of prices that is at least as large as the decrease in the predictive content of earnings. That is, the relative predictive content of earnings (R^2 of the earnings regression divided by the R^2 of the price regression) will be non-decreasing.

The result shows that an increase in NIB trading should result in a reduction in the information content of prices, which is more than the reduction in the information content of earnings. We develop the empirical research design to examine this implication.

Development of the empirical research design

We consider the three, five, seven and ten year future horizons to proxy for fundamental value. The interim period flows are measured using the ex post realized dividends or earnings[10]. We use actual ex post realizations rather than a combination of contemporaneous analysts' expectations and corresponding valuation model because analysts' forecasts introduce noise due to institutional factors, which are not related directly to the fundamental value (see Odean, 1999; Greene and Smart, 1994). More importantly, the effect of these factors cannot be objectively determined. In the absence of better proxies, the terminal value component of the fundamental value is measured using the future market value as an unbiased estimator of the flows beyond the chosen horizon. One advantage of choosing the future market value as the terminal value is that it is indisputably of interest to investors, because it determines the investors' holding period returns. The predictive ability of current earnings vis a vis prices with respect to holding period returns should be of interest to investors on its own merit independently of the assessment of prices as benchmarks. Also, since we use varying time horizons for the interim flows, the impact

[10] We use earnings, viewed as annualized cash flow, to provide supportive evidence in light of the relatively small size of the dividend-paying sample of firms. The discounting of earnings, coupled with the subtraction of their future value from the future price proxying for terminal value as will be explained below, is consistent with the earnings (viewed as approximating annualized cash flows) being held as non interest-bearing cash from one year to another.

of noise in stock prices used to proxy for terminal value is mitigated by using long time-series of interim realized flows, which are not distorted as much by NIB trading. [11]

We adopt two perspectives for the fundamental value. Under the first, we consider the discounted value of future flows and terminal values, and under the second, we consider the undiscounted value of future flows and terminal values. The first perspective views the fundamental value as the vector of present values of future realizations of dividends or earnings, and of the terminal value. The resulting vector of present values incorporates the effects of firm-specific risk associated with payoffs as well as other factors that affect the value to investors of the security. An example is the effects of liquidity traders who, by supplying liquidity to the market, decrease transaction costs of trading and hence, enhance the security's value irrespective of the payoffs (see, for example, Saar, 2000). The discount factor (*R)* is measured as one plus the average actual return in the preceding three years. To test for robustness, we also use constant discount rates of zero and 10%. The results do not change qualitatively.

Under the second perspective, where we consider the undiscounted vector of interim flows (dividends or earnings) and terminal value, the measured proxy for fundamental value is not affected by risk or factors such as liquidity trading. Under this perspective, the tests should reveal the relative information content embedded in prices or earnings with respect to the magnitude of future payoffs. In a sense the first perspective should bias the finding against earnings, since it includes more of the factors in fundamental value that are also embedded in stock price (risk, liquidity, etc.) but not in earnings; whereas, under the second perspective, the two competing information signals,

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[11] It is important to emphasize this point. It could be argued, for example, that since NIB trading decreases the information content of stock prices, using future stock price as an explanatory variable would increase the measurement error of the proxy we use as an indicator of fundamental value. , There are two reasons why using this proxy will not distort our results. First, including "future" realized flows preceding the future date on which future price is used as proxy for terminal value mitigates the decrease in information content of the stock price proxy, hence making the combination of explanatory variables a better indicator of value. We should add that we include as many future years of interim realized flows as is consistent with reasonable sample sizes. We estimate the models using up to 15 future years of interim realized flows (and a correspondingly smaller sample) with unchanged results (see footnote 17 below). Second, and more importantly, future prices are used as proxy for terminal value both in the model where the stock price is dependent variable and in the model where earnings are the dependent variable. The "mitigated" noise inherent in the future price proxy is common to both regressions, thus pitting the predictive content of earnings against that of price on a "level playing field". Clearly, this does not bias results in favor of our alternative hypothesis.

price and earnings, are placed on a more equal footing: both compete on reflecting the predictive content with respect to future realizations. Under this second perspective, the discount factor *R* equals one.

We do not aggregate the vector of future flows and proxy for terminal value (whether individually discounted or undiscounted) into one measure of proxy for fundamental value so as to avoid introducing implicit assumptions regarding the weights to attach to the horizon-varying flows. Estimation uncertainty surrounding more distant flows can affect the theoretical weights in ways we cannot objectively determine. In other words, by aggregating the future flows and the terminal value, we would implicitly assume a specific set of weights.[12] Therefore, our tests are based on reverse regressions that utilize the non-aggregated vectors of future flows and terminal value as independent variables.[13]

Specifically, we estimate the following equations to assess the predictive content of earnings and prices for *n=2, 4, 6, 9*.

$$NI(t) = k_0 + S_{i=1,n}\, k_i\, [FL^m(t+i)/R(t)^i] + k_{n+1}\, [\{MV(t+n+1) - I\text{´}FV[FL^m\,]\,(t+n+1)\}/R(t)^{(n+1)}] + error \quad (1)$$

$$MV(t) = k_0 + S_{i=1,n}\, k_i\, [FL^m\,(t+i)/R(t)^i] + k_{n+1}\, [\{MV(t+n+1) - I\text{´}FV[FL^m\,]\,(t+n+1)\}/R(t)^{(n+1)}] + error \quad (2)$$

where

$FL^m(t)$ is the interim flow in period *t*, with *m=1* denoting dividends *(DIV)*, and *m=2* denoting Net income (*NI*);

$FV[FL^m]$ is the future value of interim earnings flows

NI(t) is the net income for the fiscal year ending in year *t*;

DIV(t) is the dividend for the fiscal year ending in year *t*;

MV(t) is the market value three months after the fiscal year ending in year *t*.

R(t) is the discount factor; *I* is an indicator variable with *I=0* for *m=1,* and *I=1* for *m=2.*

The future value of interim earnings flows is deducted from the terminal value, to avoid the double counting of reinvested earnings.

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12 Nonetheless, we provide the results of preliminary analysis that includes the aggregated fundamental value as a dependent variable.

13 In Appendix A, we show analytically that the R^2 of the reverse regression is monotone increasing in information content.

To test whether the predictive content of prices has increased due to the use of non-accounting based information, we purge the information contained in earnings from stock prices and consider the “other information” that is contained in stock prices. The basic idea is that stock prices incorporate information on future earnings potential extracted from an information set that includes earnings and other non-accounting-based sources.[14] Thus, to assess the predictive content of accounting-based-earnings information relative to other information sources, we need to purge the predictive content of earnings from stock prices. The predictive content of earnings (*PNI)* is computed as the predicted value of *NI* from equation (1). That is,

$$PNI(t) = k_0^* + S_{i=1,n}\, k_i^*[FL^m(t+i\_/R(t)^i] + k_N^*[\{MV(t+n+1) - I\acute{}FV[FL^m\,]\,(t+n+1)\}/R(t)^{(n+1)}] \quad (3)$$

where the estimates $\{k_0^*,\ k_i^*,\ k_N^*\}$are obtained from equation (1). Since stock prices incorporate both accounting-based earnings and non-accounting-based information, we need to purge from prices the predictive content of the accounting-based information. Prices will impound the predictive content that is contained in the accounting-based-earnings information. The extent to which prices impound this predictive content is estimated from the following equation

$$MV(t) = q_0 + q_1\, PNI(t) + error \quad (4)$$

where the error in equation (4) represents the private, non-earnings-related, information acquired by traders as well as the effects of NIB trading. Using the estimates from equation (4) we obtain a stock price-based-measure that contains non-accounting information as well as NIB noise (*NEPS*). Specifically,

$$NEPS(t) = MV(t) - [\, q_0^* + q_1^*\, PNI(t)], \quad (5)$$

where $\{q_0^*, q_1^*\}$ are the estimates obtained from equation (4) .

A prevalent belief held by accounting researchers is that accounting has been losing its value-relevance in part because more value-relevant information from other sources has

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[14] In this paper, accounting earnings is viewed as a summary of the accounting information. To the extent other non-earnings accounting information is not effectively summarized in earnings, it will be embedded by this research design in what we refer to as non-accounting-based sources. While this is obviously inconsistent with the label we chose for the "other" information, it does not detract from the validity of the

become available to traders. That is, the coincidence of the emergence of competing value-relevant information, and the failure of accounting reporting and disclosure models to incorporate value-relevant information is generally believed to have decreased the value-relevance of accounting information over time. NEPS furnishes a measure of the information contained in stock prices derived from non-accounting sources.

Thus, we can assess whether the predictive content of NEPS has been increasing over time, as has been generally argued by some accounting researchers.

To summarize, we estimate the following models for $n=2, 4, 6, 9$:

Model Am:

$$NEPS(t)=a_0+S_{i=1,n}\, a_i\, [FL^m(t+i)/R(t)^i]+ a_{n+1}\, [\{MV(t+n+1) - I\acute{}FV[FL^m\,]\,(t+n+1)\}/R(t)^{(n+1)}] + error$$

Model Bm:

$$MV(t)= b_0+ S_{i=1,n}\, b_i\, [FL^m\,(t+i)/R(t)^i] + b_{n+1}\, [\{MV(t+n+1) - I\acute{}FV[FL^m\,]\,(t+n+1)\}/R(t)^{(n+1)}] + error$$

Model Cm:

$$NI(t) = c_0+ S_{i=1,n}\, c_i\, [FL^m(t+i)/R(t)^i] + c_{n+1}\, [\{MV(t+n+1) - I\acute{}FV[FL^m\,]\,(t+n+1)\}/R(t)^{(n+1)}] + error$$

where $FL^m(t)$ is the interim flow in period t , $m=1,2,$ with $m=1$ denotes dividends *(DIV)*, and $m=2$ denoting Net income (*NI*);

NEPS(t) is the non-accounting-based information contained in stock prices;

NI(t) is the net income for the fiscal year ending in year *t*;

DIV(t) is the dividend for the fiscal year ending in year *t*;

$FV[FL^m]$ is the future value of interim earnings flows

MV(t) is the market value three months after the fiscal year ending in year *t*.

R(t) is the discount factor;

I is an indicator variable with $I=0$ for $m=1$, and $I=1$ for $m=2$.

We scale all the variables by Total Assets (*TA)* in year *t*, to control for scale effects (see Brown et. al., 1998).

The results from the analytical model in Appendix A, leads to the following hypotheses:

Hypothesis

1) ***The R^2 of Model C is higher than the R^2 of either Models A or B.***
2) ***The ratio of R^2 of Model C to Model A is increasing over time.***

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inferences. If earnings can do better than prices or NEPS, then surely earnings plus other accounting information will do better than prices or non-accounting-related information contained in prices.

3) The ratio of R^2 of Model C to Model B is increasing over time.

As discussed earlier, all three hypotheses are a direct consequence of the increase in non-information based trading. To test for the plausibility of NIB trading being associated with the relatively steeper decline in the predictive content of prices, we measure the average trading activity (*MVOL*) as the average percentage of common shares traded in year *t*. Chiang and Venkatesh (1988) show that trading volume is highly negatively correlated with bid-ask spreads. A higher bid-ask spread is associated with informational-difference-related transaction cost (see Glosten and Milgrom, 1985). Conversely, when the specialist (market maker) faces less informed traders, the bid ask spread would decrease. In essence, the average trading volume is a proxy for the increase in liquidity/ NIB trading. In addition, we control for other explanations for the decline in R^2 by using variables similar to those used in Collins et. al. (1997). Specifically, we define MLOSS as the percentage of firms whose operating income was negative each year; MONETIME is the percentage of firms with special items each year and MINTANG is the percentage of firms operating within the intangible-intensive industry as defined in Collins et. al. (1997). We estimate the following model.

$$R^2(\text{Model } i) = g_0 + g_1\, MVOL + g_2\, MLOSS + g_3\, MONETIME + g_4\, MINTANG + error \quad (6)$$

We hypothesize that the g_1 will be negative and significant for Models A and B, due to the increase in NIB trading. We proceed to describe the sample selection and provide some preliminary results.

III. Sample selection and results

The sample consists of all firms that belong to the Primary, Secondary, Tertiary, Full Coverage and Research Annual Industrial files in the Compustat Annual Database from 1960 to 1997. We required that data on Net Income, *NI* [data item 172], Total assets, *TA* [data item 6] and Total liabilities, *TL* [data item 181] be available for six years subsequent to the test year and that Total assets be non-negative.

Firms that met these criteria were then required to have stock price data and shares outstanding data in the CRSP monthly file for the last day of the third trading month after the firm's fiscal year end, and for the same trading month for the previous four years. This selection process yields 17,140 firm-year observations. We deleted the top and bottom ½ percent of observations each year and also observations that have a studentized residual of greater than 4 standard deviations from zero.[15] To keep the tests comparable, we use the final sample of 16,951 firm-year observations for estimating each Model.

We measure the discount factor *R(t)* as the average annual return plus 1 over the past three years.[16] Specifically, we have

$$R(t) = 1/3[\{MV(t-1)/MV(t-2)\} + \{MV(t-2)/MV(t-3)\} + \{MV(t-3)/MV(t-4)\}] \tag{7}$$

Table 1 provides descriptive statistics on the final sample.

Insert Table 1 here.

From Table 1 we see that (a) the number of firms is higher in the 80s than in the 60s and (b) both the mean and the standard deviation of all statistics are higher in the 80s than in the 60s. Specifically, we observe a striking increase in the mean (380%), median (170%) and standard deviation (444%) of firm size measured in terms of total assets, accompanied by a large increase in skewness (the ratio of mean to median increased from 3 to 6.7). The maximum firm size increased 5.3-fold. A symmetric pattern emerges in the rate of return distribution: the mean 3-year average rate of return plus 1 increased by about 6% between the 60's and the 80's, the median increased by 5%. The ratio of mean-to-median (1.04) and

[15] We first delete the top and bottom half-percent of the scaled variables and then delete the outliers based on the studentized residuals.
[16] We estimated the models also with a constant discount factor of R=1.10%. The results were similar to those reported in the paper.

(1.05), respectively, did not exhibit any change. The 80's distribution of return plus 1 is not much more spread than in the 60s. The standard deviation was 0.32 in the 80's versus 0.28 in the 60's. If these 3-year average discount factors are viewed as reflecting equilibrium rates of return, the implication is that of a moderate increase in risk over time. Next we provide some preliminary evidence with respect to the time trend of the R^2.

Some preliminary evidence

Before proceeding to estimate Models A1, B1, C1 and A2, B2 and C2, we provide some preliminary evidence that would help compare our results with that of Collins et. al. (1997) and also, provide a sensitivity check for aggregating the fundamental value. Specifically, we estimate the following models.

Model A0: $FNDV(t) = a_0 + a_1\ NAPS(t) + error$

Model B0: $FNDV(t) = b_0 + b_1\ MV(t) + error$

Model C0: $FNDV(t) = c_0 + c_1\ BV(t) + c_2\ NI(t) + error$

where $FNDV(t)=S_{i=1,n}[DIV(t+i)/R(t)^i] + [MV(t+n+1)/R(t)^{(n+1)}]$

$NAPS(t)$ is the non-accounting-based information contained in stock prices and is estimated as the residual from $MV(t) = k_0 + k_1\ BV(t) + k_2\ NI(t) + error$;

$NI(t)$ is the net income for the fiscal year ending in year t;

$DIV(t)$ is the dividend for the fiscal year ending in year t;

$MV(t)$ is the market value three months after the fiscal year ending in year t.

$R(t)$ is the discount factor.

We include book value as independent variable as well as earnings, Table 1A presents the results from estimating Models A0, B0 and C0.

Insert Table 1A here.

Panel A (B) presents the results when the fundamental value is computed using the five (ten) year future horizon. In Panel A, the ratio of R^2 of Model C to A, is greater than one for each of the ten test year periods and is increasing over time; 1.35, 2.11 and 3.01. The ratio of R^2 of Model C to Model B is less than one for the 60s, close to one in the 70s and greater than one in the 80s; 0.68, 0.91 and 2.08. This is consistent with our hypothesis of increased NIB trading noise included in the stock prices. The partial F-test presents a similar picture. Specifically, including stock price as an additional variable in Model C0, does not increase the explanatory power of the model in a statistically significant manner in the 80s, while in the 60s and 70s on average including the price improved the explanatory power of the model. The ten-year horizon results provided in Panel B lends stronger support for the hypothesis. For the ten-year horizon, the partial F-tests are insignificant for all three decades, and the ratios of the R^2 of Model C to B (A) are all above one and show an increasing trend, as hypothesized.

For the main analysis, where we resort to the reverse regressions, we do not include book value and focus on earnings as the summary statistic, consistent with its wide use by the analysts and the press. To this extent, we employ a harsh test, which biases the results in favor of prices.

Results on predictive content

The means of R^2 for the 60s, 70s and 80s of Models A, B and C for n = 4 are provided in Table 2.[17]

Insert Table 2 here.

The predictive content of earnings is significantly higher than that of prices and NEPS across all decades. When flows are dividends, the adjusted R^2 with discounting is 19%, 16%, and 38% (see top of Panel A) higher than that of prices in the 60's, 70's, and 80's, respectively. Similarly, when flows are net income, the adjusted R^2 with discounting is 43%, 44%, and 49% (see top of Panel B) higher than that of prices in the 60’s, 70’s and 80’s , respectively. The respective comparisons without discounting are 4%, 12%, and 37% (dividend flows), and 17%, 17%, and 23% (net income flows). The R^2 of the earnings regression is statistically higher than the price and NEPS regressions as evidenced by the G-statistic. This observation, thus, supports each of our three primary hypotheses.[18]

The relatively higher rate of decline in the predictive content of prices is reflected in the increase in the ratio of R^2 of model C over model B, from 1.18 to 1.37 for dividend flows with discounting, 1.03 to 1.36 for dividend flows without discounting, 1.41 to 1.48

[17] The coefficients on the independent variables are not reported since the focus is on R^2s as the measures of information content. Also, the estimates of the coefficients are influenced by high collinearity among the independent variables.

[18] We also estimate our models with the vector of dividends and earnings for 14 years and the stock price in the 15th year. The average number of observations for the 60s is 183 and for the 70s is 314. The ratio of Model C’s R^2 to Model B’s R^2 in the 60s is 1.23 and in the 70s is 1.42.

for net income flows with discounting and 1.17 to 1.23 for net income flows without discounting. The increase in the ratio of R^2s is more striking when the earnings R^2 is compared with the NEPS R^2;specifically, the ratio increases from 5.52 to 10.72 for net income flows with discounting and 2.61 to 3.97 for net income flows without discounting.

Year-by-year graphs

Figure 1 provides the graph of the R^2 of Models A, B and C from 1960 through 1989.

Insert Figure 1 here.

The predictive content of NEPS is declining over time (see Figure 1a). The decline is more pronounced for n = 2 and almost negligible for n = 6. The degree to which the future values are embedded in the information signal NEPS, i.e., the R^2, for almost every year is attenuated as the horizon over which the independent variables are measured is lengthened. For example, in 1960, the R^2 is slightly above 0.35 for n = 2, a little below 0.25 for n = 4, and 0.05 for n=6. This reflects the decaying explanatory power of the model as the terminal value proxied by market value at the end of the horizon is farther from the time at which the information signal is observed. This suggests that the notion of more non-accounting based relevant (to fundamental values) information being incorporated in prices in recent years than in the earlier years is not supported.

Figure 1b provides the temporal R^2s of Model B. For Model B, the temporal decline in R^2 is not as pronounced as in the case of NEPS (Figure 1a). This observation suggests that the contribution of earnings to the predictive content of prices is non-trivial. The R^2 of prices (Figure 1b) are clustered around 0.60 in the beginning of the sample period and end up at around 0.25-0.3 at the end of the sample period. Figure 1c provides the temporal R^2s for Model C. Figure 1c, where the dependent variable is earnings, exhibits the least temporal decline in R^2, from a little less than 0.8 to about 0.4. By and large, Figure 1 indicates that the decline in the earnings R^2 is slower than the decline in the NEPS and price R^2s.

To assess the relative rate of decline in the R^2 of Models B and C, we plot the ratio of the R^2 of Model C to the R^2 of Model B in Figure 2.

Insert Figure 2 here.

Figure 2 indicates the predictive content of earnings has been always (almost always) superior to that of prices in the medium and long horizon (short horizon), in the sense that the ratio of R^2 is always (almost always) greater than 1. This implies that while the predictive content of both prices and earnings have declined over time, the predictive content of prices has declined at a slightly faster rate than the predictive content of earnings.

Some firms have missing dividend data, which we assume as zero dividend firms for the analysis.[19] Since the results of the net income model are consistent with those of the dividend model for the full sample, we provide the results based on the earnings model for all further tests.

Partitioning on size

We estimate Models A2, B2, and C2 for the small and large firms. The low (high) half of market value for each year constitutes the small (large) firms. The results are provided in Table 3.

Insert Table 3 here.

Focusing on Models C2 and B2 with discounting, the ratio of the R^2 of C2 over that of B2 increases more for the small firms than for the large firms. In fact, the ratio is almost stable for the large firms. Without discounting, the ratio increases for both small and large firms (8% and 4% respectively.) Also, the ratio is greater than 1 for the three time periods and across both size groups under both discounting and non-discounting. This indicates that the pattern of temporal decline in R^2 does not appear to be driven purely by size.

The R^2 across all three decades are consistently higher for the large firms than for the small firms. The relative predictive content of prices of the large firms vs. small firms in the 80s with discounting is 2.76 (R^2=43.08/ R^2=15.59), which is 1.70 times that of the relative predictive content of earnings over the same decade, 1.62 (R^2=51.43/ R^2=31.66.) That is, the degree to which prices are more informative about large firms' prospects (relative to small firms) is higher than the degree to which large firms earnings are more informative than small firms earnings. To speculate, this (possibly) reflects larger

[19]In cases where the dividend data is not directly available in the financial statements, Compustat codes these as insignificant or missing. Assuming that such firms are not dividend-payers is a reasonable assumption.

following and more active information gathering by sophisticated analysts and traders, and/or relatively smaller volume of NIB trading in the case of the larger firms.

Partitioning on book-to-market ratio

We estimate Models A2, B2, and C2 for the small and large book-to-market ratios. The book value is computed as the difference between total assets and total liabilities. The small (large) book-to-market ratio firms are the firms that are below (above) the median book-to-market each year. The results are provided in Table 4.

Insert Table 4 here.

For both the small book-to-market firms (the high growth firms) and high book-to-market firms (the low growth firms) the ratio of R^2 has increased over time, but more in the latter set of firms (from 1.35 to 2.69, vs. 1.53 to 1.68 for the discounted flows, and from 1.28 to 1.47 vs. 1.19 to 1.24 for the undiscounted flows.) This shows that for the low growth firms the predictive content of earnings has outpaced the predictive content of prices over time.

With the minor exception of NEPS in the 80s in the case of discounted flows, all adjusted R^2 are considerably higher in the case of small book-to-value firms, across the 3 decades and the 3 models. For example, in the 80's the predictive content of earnings is 66% higher (R^2=43.74/ R^2=26.31), and the predictive content of prices is 182% higher (R^2=25.54/ R^2=9.06)for discounted flows and 87% higher (R^2=50.35/ R^2=26.88) for undiscounted flows. This may seem counterintuitive; after all, are not the high growth firms (small book-to-market) those whose prospects are harder to predict? But, to speculate, the high book-to-market firms may be those financially distressed firms that had fallen into market disfavor (see Fama and French, 1992.) Consequently, these may be the firms that had been subjected to such market uncertainties as would make their prospects harder to predict than those of the more market-favored firms.

The relative predictive content of prices for the small book-to-market vs. large book-to-market in the 80s (discounted flows), is 1.73 times that of the relative predictive content of earnings over the same decade, 2.82(R^2=25.54/ R^2=9.06) versus 1.66 (R^2=43.74/ R^2=26.31.) The corresponding ratios for the undiscounted flows are 2.27, 1.21 times 1.87. That is, the degree to which prices are more informative about small book-to-market firms' prospects (relative to large book-to-market) is larger than the degree to which smaller book-to-market firms' earnings are more informative than larger book-to-market earnings. Possibly consistent with the size-partitioned samples, this may reflect larger following of and interest in the high growth firms among traders (inducing them to become more informed) hence making prices more informative for the small book-to-market firms.

The predictive content of small book-to-market firms' prices (earnings) deteriorated less over time than that of the large book-to-market: 49% vs. 79% (45% vs. 57%) in the discounted flows case and 36% vs. 64% (34% vs. 58%) in the case of undiscounted flows. Thus, the decline in predictive content of small book-to-market firms' signals relative to the predictive content of large book-to-market firms' signals was more pronounced in the case of prices (especially for the large book-to-market firms) than in the case of earnings. That the decline in predictive content of prices relative to that of earnings was far more pronounced in the case of the large book-to-market firms is reflected in the significant increase in the ratio of model C's R^2 to model B's R^2 in the 80s for the large book-to-market firms, whereas this ratio increased only slightly for the small book-to-market firms. Consistent with the above speculation, uncertainty surrounding "financially distressed" (large book-to-market) firms' and speculative (NIB) trading in such firms' securities may have increased in the 80's sufficiently to render prices far less informative. Clearly, further research into this question is merited.

Partitioning over industry groupings

We aggregate the market value, net income and total assets over two digit SIC codes and estimate Models A2, B2, and C2. The results are reported in Panel A of Table 5.

Insert Table 5 here.

The predictive content of earnings is higher than that of prices, and far higher than that of NEPS across all decades. The relatively higher rate of decline in the predictive content of prices is reflected in the observation that the ratio of R^2 of model C over model B increased from 1.10 to 1.19 from the 60s to the 80s in the case of discounted flows and from 1.05 to 1.07 in the case of undiscounted flows.

Panel B of Table 5 estimates Models A2, B2, and C2 for firms operating in intangible intensive and non-intangible intensive industries separately. We classify firms as being intangible intensive and non-intangible intensive in a manner similar to Collins et. al. (1997). Specifically, firms that operate in SIC codes 282, 283, 357, 367, 48, 73 and 87 are categorized as intangible-intensive.

With the exception of NEPS, adjusted R^2s are higher for intangible-intensive industries (INT) than for non-intangible-intensive industries (NONINT) across the three decades and the three models. However, in the case of undiscounted flows, intangible-intensive industries feature higher adjusted R^2s for NEPS in the 70s, for prices throughout the three decades, and for net income in the 60s.

The predictive content of earnings is uniformly higher than that of prices for both INT and NONINT industries and across all decades. The relative predictive content of prices for the INT industries vs. NONINT industries in the 80's, 1.12 (R^2= 28.18/ R^2= 25.12) is about equal to that of the relative predictive content of earnings over the same decade in the case of discounted flows, 1.15 (R^2= 42.10/ R^2= 36.70). The corresponding comparisons for undiscounted flows are 1.03 and 0.78. That is, the degree to which prices are more informative about INT industries' prospects (relative to NONINT industries) is the same as the degree to which INT industries' earnings are more informative than NONINT earnings in the case of discounted flows.

First Difference Model

For the full sample, when all variables are first-differenced, the same overall pattern with the exception of the 60's (See Table 6, Panel A). Over the 70's and the 80's, earnings differences display higher predictive content than price differences (66% higher in the 70's and 296% higher in the 80s in the case of discounted flows). The relative predictive content of earnings differences (relative to price differences) increased 5.6 fold (from 0.52 to 3.42) from the 60's to the 80s in the case of discounted flows, and 4.5 fold (from 0.49 to 2.21) in the case of undiscounted flows.

Cash flow based model

Using cash flows instead of earnings for the interim flows (i.e., net income adjusted for changes in working capital), we obtain similar results (See Table 6 Panel B).[20] Adjusted R^2 of earnings is higher than those of prices across time and models (in the 80's, the earnings R^2 is 105% (31%) higher than that of prices in the case of discounted

[20] This is a measure of free cash flow to equity under the assumption that capital expenditures are equal to depreciation and the debt to equity ratio is maintained.

(undiscounted) flows. Similarly, the relative predictive content of earnings (relative to price) has steadily increased over time: from 1.16 in the 60s to 1.98 in the 80s in the case of discounted flows and from 1.20 to 1.31 in the case of undiscounted flows.[21]

Summary of the observations

The empirical findings up to this point are summarized below.

(a) The predictive content of earnings is higher than the predictive content of prices.

(b) The predictive content of earnings has declined over time.

(c) The predictive content of prices has also declined over time.

The rate of the decline in the predictive content of prices is, in general, higher than that of earnings.Could the higher R^2 of the earnings regressions reflect merely a spurious correlation because of built-in correlation between earnings at time t, and future flows, at time $t+\tau$, $\tau>1$. For example, if the future flows included as independent variable are earnings and, if earnings are random walks, the earnings regression may spuriously exhibit a larger R^2 merely because of this fact. This does not render our conclusions invalid for the following reasons.

(1) Whatever the time-series properties of earnings or dividend, our results are valid as long as the vector of independent variables (flows of dividends or earnings and terminal price either individually discounted or undiscounted) capture the construct of fundamental value.

(2) Suppose future flows exhibit built-in correlation due to strategic smoothing by management of earnings or dividends. This may be the result of incentive-compatible endeavor by management to signal private information about the fundamental value (See Ronen and Sadan 1981, chapter 3). Consequently, any resulting correlation is a genuine reflection of the predictive content with respect to the fundamental values.

[21] We estimated the models with operating income instead of net income as well. The results were consistent with those reported here.

(3) If earnings are random walks, so are prices. And an argument related to spurious correlation can be also invoked to suggest that the price regression could yield higher R^2, because a subsequent price is included as an independent variable.

(4) Earnings have in fact been shown to be less persistent than random walks (see e.g., Kormendi and Lipe, 1987).

(5) Finally, if earnings are sticky – i.e., behave as random walks, first differences in earnings (or other flows) should be independent (non-sticky). Our results are similar with first-difference models.

Test for NIB trading and the decline in predictive content of stock prices

While the predictive content of both prices and earnings has declined, the decline has occurred at a higher rate for prices than for earnings. We test for the plausibility of NIB trading being associated with the relatively steeper decline in the predictive content of prices. We measure the trading activity (VOL) by the common shares traded in year t (data item 28) divided by the number of common shares outstanding at the end of the fiscal year. We then compute the mean trading volume (MVOL) for each year. In addition, we control for other explanations for the decline in R^2 by using variables similar to those used in Collins et. al. (1997). Specifically, MLOSS is the percentage of firms whose operating income was negative each year; MONETIME is the percentage of firms with special items each year and MINTANG is the percentage of firms operating within the intangible-intensive industry as defined in Collins et. al. (1997).

Panel A of Table 7 presents the descriptive statistics of the explanatory and control variables.

Insert Table 7 here.

We use log transformations of MVOL because it is skewed. Specifically, LNMVOL = log(MVOL). Panel B of Table 7 shows the correlation between the explanatory and control variables with the R^2. The year variable is negatively associated with the R^2 in all the models, indicating that the R^2 are indeed declining over time for each of the Models. Trading volume, loss and one-time items are also significantly associated with the decline in R^2 of the three models. The percentage of firms in intangible intensive industry is not associated with the decline in R^2, consistent with Collins et. al. (1997). Panel C of Table 7 shows the correlation among the explanatory and control variables.

Insert Table 8 here.

The results in Table 8 show that trading volume explains the decline in R^2 of the two models above and beyond the one-time items and losses. This is consistent with the NREE analysis that we presented.

IV. Concluding remarks

Past studies focused on examination of the value relevance of accounting numbers (such as earnings and book values) by documenting contemporaneous associations between the accounting numbers and market prices (levels or changes). In this paper we adopt a different approach -- one based on examining the predictive content of both earnings and price signals separately. We find that the predictive content of earnings is higher than that of prices. And while the predictive content of earnings declined over time, the predictive content of price signals declined by even more. We also find that the temporal decline in the R^2 of the price signals is associated with increases in trading volume. Coupled with the insights from our analysis of the noisy rational expectation equilibrium model, this is consistent with the observation that non-information-based (NIB) trading has caused the predictive content of prices to degrade over time. These findings suggest that price signals, having become noisier over time, may not be the appropriate benchmark for gauging the information content of accounting earnings.

<u>Appendix A</u>: Relative information content of earnings and prices

The Model

We consider a four-date, three-trading-rounds, noisy rational expectations equilibrium model of trading and prices with a risky asset, a riskless bond, and many traders. The risky asset is a normally distributed random liquidating value of x units (per share) with mean 0 and variance s_x^2 and is realized at the end of the final period, i.e., time t_3. The riskless bond B yields a payoff of one at time t_3. Each trader i, starts with an initial endowment of the riskless bond, B_i. The details of the information process on the liquidating value of the risky asset, x are as follows. Each trader acquires private information, y_{i_o}, before markets open for trade. Private signals about asset values are identically and independently distributed across traders, and given by: $y_{i_o} = x + \gamma_I$ where $\gamma_i \sim N(0, s_{e_i}^2)$, and are independently distributed from x. For simplicity, we assume that the precision of the private signal is identical across investors, which implies that $s_{e_i}^2 = s_{e_j}^2 = s_e^2$ for all i and j. One round of trade then takes place, with the equilibrium price, P_0, at time t_0 providing an additional source of information. The demands for the risky and riskless securities are chosen to maximize the expected utility of end-of-final-period-wealth with the knowledge among traders that there will be further rounds of trading following anticipated future public disclosures available at time t_1 and time t_2. The public information disclosure at time t_1 and t_2, denoted by y_1 and y_2, are defined respectively as: $y_1 = x + u_1$ and $y_2 = x + u_2$.

The public signals reflect the liquidating value with noise, u_1 and u_2 respectively, in which $u_i \sim N(0, s_u^2), i = 1,2$. We allow for the possibility of correlation between u_1 and u_2. The risky asset yields a payoff of x at time t_3, when the final period wealth W_{i_3} is consumed. Therefore, W_{i_3} consists of the trader's initial endowment, B_i, plus the returns on investment in the risky asset in periods 0, 1 and 2. Denoting these investment levels by z_{i_0}, z_{i_1}, and z_{i_2}, the realized returns on these holdings are: $z_{i_0}(P_1 - P_0)$, $z_{i_1}(P_2 - P_1)$, and $z_{i_2}(x - P_2)$ respectively. Therefore, ending wealth W_{i_3} can be expressed as:

$$W_{i_3} = B_i + z_{i_0}(P_1 - P_0) + z_{i_1}(P_2 - P_1) + z_{i_2}(x - P_2).$$

Traders' utility functions are negative exponential in end-of-final-period wealth W_{i_3}, with a constant absolute risk aversion coefficient r_i expressed as

$$EU(W_{i_3}) = -E[\exp(-r_i\{B_i + z_{i_0}(P_1 - P_0) + z_{i_1}(P_2 - P_1) + z_{i_2}(x - P_2)\})]$$

Each trader has access to private and public information sources. Private information, y_{i_0}, is acquired at time t_0; public announcement y_1 is available at t_1; and public announcement y_2 at t_2. In addition, the equilibrium prices P_0, P_1, and P_2, also provides information to the traders. Therefore, the information set available to trader i at times t_0, t_1, t_2, denoted by I_{i_0}, I_{i_1}, and I_{i_2}, respectively, are given by:

$$I_{i_2} = \{y_{i_0}, y_1, y_2, P_0, P_1, P_2\}; I_{i_1} = \{y_{i_0}, y_1, P_0, P_1\}; I_{i_0} = \{y_{i_0}, P_0\}.$$

The model is one of noisy rational expectations where aggregate supply is uncertain. Let Z_0, Z_1, Z_2, denote the aggregate per-capita supply of the risky asset in the respective periods. We assume that the aggregate supply of the risky asset at t_0 is given by Z_0 and that there are independent shocks, t_t, in each period t_j for j ³ 1. We assume the following structure for the aggregate uncertain supply at time t_j j ³ 1, Z_j

$$Z_j = Z_0 + bt_j, \qquad 0 \le b < \infty$$

We set the variances $s^2_{t_j} = s^2_t > 0$ for every t_j without loss of generality and consider the two limiting cases (i) $b = 0$ and (ii) $b => \infty$. The first case leads to a constant supply uncertainty $Z_t = Z_0$, while in the second case the persistent component can be ignored and the noise in traders' supply is independent across time.

We make all the standard assumptions for the rational expectations model (see, Admati, 1985). Specifically, we assume that all variables are jointly normal and that the equilibrium we seek involves price functions that are linear in signals and aggregate supply of the risky asset. We also assume, as is common in rational expectations studies, a "large" economy where individual traders are price-takers; the average of the traders' private information is the true underlying asset value x and the average of the trader's net demands (or supplies) is equal to the per-capita excess supply (or demand) Z_t.[22]

Equilibrium solution

For the above model, it is possible to derive one closed form equilibrium solution, which is useful for providing insights into the relative information content of the earnings and prices (see Kim and Verrecchia, 1991 and Dontoh and Ronen, 1993). The determination of the equilibrium involves a backward-induction, dynamic programming approach beginning with the determination of demands for the risky security following the second public announcement. We then solve for individual demands in earlier periods, treating future demands as random variables. This procedure leads to an equilibrium with the following prices

$$P_0 = V_0(s + s_q)q_0; P_1 = V_1(s_u y_1 + (s + s_q)q_0) - r K_1 bt_1$$

$$P_2 = V_2\left(\frac{s_u}{1+r}(y_1 + y_2) + (s + s_q)q_0\right) - rV_2 bt_1$$

where

[22] If there are N traders, in equilibrium, the average per-capita noisy supply (or demand), Z_t satisfies Z_t = $[1/N]\sum_{i=1}^{n} z_{i_t}$ where z_{i_t} denotes trader i's demand in period t. For the average private signal, we use the assumption of "many traders" and invoke the strong law of large numbers to write: $Lim_{N \to \infty}$ $[1/N]\sum_{i=1}^{n} y_{i_0}$ $=x$. Also, note that many other studies extend this approach to a continuum of traders and write $Z_t = \int_0^1 z_{i_t} di$ and $x = \int_0^1 y_{i_0} di$ despite some associated technical complications (see Judd, 1985).

$$K_1 = (V_1 - V_2) + \frac{r_2 V_2^2 b^2 s_r^2}{1 + r_2 V_2^2 b^2 s_r^2} V_1 = \frac{1}{\frac{1}{V_2} + r b^2 s_r^2}$$

$$V_2 = \frac{1+r}{(1+r)(s_x + s + s_q) + 2s_u}; \quad V_1 = \frac{1}{s_x + s + s_q + s_u}; \quad V_0 = \frac{1}{s_x + s + s_q};$$

$$s_x = \frac{1}{s_x^2}; \quad s = \frac{1}{s_e^2}; \quad s_u = \frac{1}{s_{u1}^2} = \frac{1}{s_{u2}^2}; \quad s_{Z_0} = s_Z = \frac{1}{s_{Z_0}^2}; \quad s_{q_0} = s_q = \frac{s^2 s_Z}{r^2}; \; s_{u1}^2 = s_{u2}^2 = s_u^2, \; r = Cov\{u_1, u_2\},$$

$q_o = x - (r/s)Z_0$, $s(.)$ denote the precision, and V_j denotes the posterior variances of x at time j.

The equilibrium holding levels, z_{jt}, are given by[23]

$$Z_{i_2} = \frac{s}{r_i}(y_{i_0} - q_o) + \frac{r}{r_i} t_2 \quad ; Z_{i_2} = \frac{s}{r_i}(y_{i_0} - q_o) + \frac{r}{r_i} t_1 .$$

Thus, the volume is given by

$$(Z_{i_2} - Z_{i_1}) = \frac{(s_i - s)}{r_i}(P_1 - P_2) + \frac{r}{r_i}(t_2 - t_1)$$

The volume formula above has a liquidity term in addition to that derived in Kim and Verrecchia (1991). It follows that there is some trading volume even if there is no price change; such trading is driven by variations in the supply of the risky asset rather than informational effects. Discussions of trading volume based on heterogeneous interpretations of public signals are provided in Dontoh and Ronen (1993) and Kandel and Pearson (1995).

Development of a measure of information content of the accounting signal

We define the total "information content" (IC) of the set of information signals at time t, $\{I_t\}$ about the liquidating value of a risky asset x as the inverse of the conditional variance of x given the information set I_t, i.e., $IC = [1/Var(x½I_t)] = [1/V_t]$. The relative contributions of individual information variables to total information content can be determined by evaluating the change in total information content with respect to changes in the precision of these signals. Inspection of the expressions for V_1 and V_2 shows that total information content, as defined above, is increasing in the precision of the price signal incremental to earnings, s_{q_0} (henceforth, a net-of-earnings price signal, NEPS) and of the earnings signal, s_u. It follows that $[dIC/ds_u] = 2$ and $[dIC/ds_{q_0}] = 1+r$; hence, $[dIC/ds_u] > [dIC/ds_{q_0}]$, since $r < 1$, where r is the correlation coefficient of successive earnings signals y_t and y_{t+1}. The inequality implies that a one-unit increase in the precision of earnings increases the total information content by more than a one-unit increase in the precision of NEPS.

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[23] Kim and Verrecchia [1991] consider a related but different setting where the precision of the private signals varies across traders but the supply uncertainty consists only of the persistent component Z_0, that is, there are no changes comparable to our t_1. Kim and Verrecchia then show that the level of trade is the variance of the traders' private information multiplied by the price change $P_2 - P_1$.

Observation A1: *The impact of an increase in the precision of earnings is more than the impact of an increase in the precision of net-of-earnings prices (NEPS).*

Observation A1, is a direct consequence of the fact that s_{q_0} depends on the noise in NEPS arising from non-information-based (NIB) trading while s_u is independent of the noise in NEPS.

Reverse regression and implications for the relative information content of earnings and prices

The R^2 of the regression of a dependent variable x (liquidating dividend – fundamental value) on independent variables y (earnings) and P_t (price at time t) is the ratio of the variability in x explained by y and P to the total variability of x. Specifically, this ratio is expressed as $(Var(x) - Var(x|y,P))/Var(x) = 1- Var(x|y,P_t)/Var(x)$. It follows directly that an increase in the information content of the information set $\{y,P_t\}$ about x, defined as $[1/\mathrm{Var}(x|y,P_t)]$, should result in higher a R^2, for a given $Var(x)$. Therefore, to assess the information content of prices and earnings, a regression of x on y and P_t would suffice.

However, since x, the liquidating dividend (fundamental value) is not observable for going concern firms, ex-post observed variables such as future dividends or earnings and price are used as proxy for x. This empirical design will essentially investigate the predictive ability of current information signals with respect to the chosen future variables. Note that our research question requires an assessment of the relative predictive ability of price signals and earnings signals over time. We can investigate this by regressing current price and earnings signals on future variable realizations (surrogating for the fundamental value of the firm), separately. We examine the relation between the R^2 derived from these reverse regressions and the information content.

For the empirical research design that examines reverse regressions, we need to derive theoretical implications for the relative R^2*s* of the earnings and price regressions on the liquidating value. We establish that the relation between the R^2 and the information content of information variables in the normal regression of x on y and P_t is the same as in the reverse regressions of y on x and P_t. Let $R^2(P_t)= (Var(P_t) - Var(P_t|x))/Var(P_t)$ be the predictive content of the price signal at time t and $R^2(y_t)= (Var(y_t) - Var(y_t|x))/Var(y_t)$ be the predictive content of earnings signal at time t. It is relatively straightforward to show that $\partial R^2(y)/\partial s_u = [s_u s_x/(s_u + s_x)] > 0$, and hence, the predictive content of the earnings signal increases in its information content (precision). Determining the relationship between $R^2(P_t)$ and the information content of prices s_p, where $s_p = [1/Var(x|P_t)]$, is more involved, since P_t is endogenously determined and depends on other information signals. From the above, the equilibrium price at time $t=2$, following the release of the second period earnings report is $P_2 = V_2\left(s_u(y_1 + y_2) + (s + s_q)q_0\right) - rV_2bt_1$. P_2 may be expressed in orthogonal form as

$$P_2 = A\,x + B(u_1+u_2) + C\,Z + D t_2,$$

where

$$A = V_2\left(2s_u + (s + s_q)\right) = [\left(2s_u + (s + s_q)\right)/\left(2s_u + (s + s_q + s_x)\right)],$$

$B = V_2\left(s_u(y_1 + y_2)\right)$,

$C = -V_2\left((s + s_q)B_0\right)$, and

$D = -rV_2b$.

Substituting for $Var(P_2) = A^2 (1/s_x) + B^2 (1/s_u) + C^2 s_z^2 + D^2 s_t^2$ and $Var(P_2|x) = Var(P_2) - (Cov(P_2, x))^2 / var(x)$ and setting $r = 0$ for simplicity[24], we have

$$R^2(P_t) = \frac{A^2 s_x^2}{Var(P_2)}.$$

Let $W = 1/[Var(x \mid P_t)]$ denote the *IC* of the price signal and observe that $R^2(P) = 1 - [1/Var(x)]\{1/W\}$ which is clearly increasing in W for a fixed $Var(x)$. Furthermore, numerical analysis shows that $\partial R^2(y)/\partial s_z^2$ is decreasing in s_z^2. This leads us to the following Observation.

<u>Observation A2</u>: *$R^2(P_t)$ is (a) increasing in $[1/Var(x \mid P_2)]$, the information content of the price signal, (b) increasing in s_u, the information content (precision) of the earnings signal s_u, and (c) decreasing in s_z^2 the variance of NIB trading.*

The main observation from the above analysis is that the relation between the R^2 and the information content of earnings and prices is qualitatively the same in the normal regression of *x* on *y* and P_t and in the reverse regressions of *y* on *x* and P_t on *x*.

Putting the above arguments together, it follows that the predictive content of earnings increases in its precision. On the other hand, whereas the predictive content of the price signal increases with information content, it decreases with the variance of NIB trading. At the same time, trading volume increases both in the earnings precision, and in NIB trading noise s_z^2.[25] Hence, an increase in trading volume due more to an increase in the level of NIB trading than to an increase in information signals' precision will be consistent with lower R^2s. That is, we would expect a negative relation between R^2 and the level of trading volume when increases in trading volume are due to NIB trading and not to increased information content of publicly available signals. A decrease in the predictive content of price signals, coupled with an increase in trading volume is consistent with the increase in volume resulting from NIB trading and not from a higher information content of signals. In other words, an increase in NIB trading is consistent with a lesser predictive content of price. But increases in the NIB trading do not affect the precision of earnings. These arguments are summarized in the following Observations (and also at the beginning of the research design section).

<u>Observation A3</u>: *An increase in trading volume and a decrease in the predictive content of earnings will be associated with a decrease in the predictive content of prices that is at least as large as the decrease*

[24] Setting $r = 0$ facilitates the derivations and does not affect the results.

[25] Numerical analysis reveals that $[dVol / ds_u] > 0$ and $[dVol / ds_z^2] > 0$. Details are available from the authors upon request

in the predictive content of earnings. That is, the relative predictive content of earnings (R^2 of the earnings regression divided by the R^2 of the price regression) will be non-decreasing.

Appendix B[26]: Test for the equality of R^2

We assume that the errors in Models A and C are independent. In such a case the error in Model A reflects the effects of NIB trading; while the error in Model C reflects the noise injected as a result of strategic or inadvertent use of GAAP. Note that the error in Model B is a composite of both these errors. Let R_i^2 denote the R^2 from Model *i* (for *i*=A,C) with *K* predictors and *N* observations for each year. Denote the true population R_i^2 value as $\mathbf{R}_i$. We know that the conditional distribution of $\frac{R_i^2}{1-R_i^2}\times\frac{N-1-K}{K} = G_i^2$ is a non-central *F* distribution with (*K*, *n* - 1 - *K*) degrees of freedom and non-centrality parameter $\delta_i = \left[\beta_i' \, A_{22,i} \, \beta_i\right]/\sigma_i$, where b_i is the true regression coefficient, $A_{22,i}$ corresponds to the $X'X$ matrix, and s_i is the standard deviation of the error term (see Anderson, 1958, p93).

We wish to test **H$_0$: R$_A$ = R$_C$** or its equivalent **H$_0$:** $d_A^2 = d_C^2$. Consider the function

$$G = \frac{G_A^2}{G_C^2} = \left[\frac{R_A^2}{1-R_A^2}\right]\left[\frac{1-R_C^2}{R_C^2}\right].$$

The G-statistic is the ratio of two non-central *F* distributions. Specifically, the distribution of G the first brackets is a double non-central *F* distribution, and the factor in the second brackets is an ordinary central can be represented as $\left[\frac{\left(c_{K,A}^2(d_A^2)\right)/K}{\left(c_{K,C}^2(d_C^2)\right)/K}\right]\left[\frac{\left(c_{N-1-K,C}^2\right)/N-1-K}{\left(c_{K,C}^2(d_C^2)\right)/N-1-K}\right]$. The factor in *F*. Thus, the distribution of G is $F_{K,K}(d_A^2, d_C^2)F_{N-1-K,N-1-K}$ and the two factors are independent. Since the second factor is an ordinary central *F*, we can best address this problem by conditioning on the observed value of this central *F*. An approximate distribution of the first factor is given by $\left[\frac{1+\left(d_A^2/n_A\right)}{1+\left(d_C^2/n_C\right)}\right]F_{n_A,v_C}$ with $n_i = \frac{\left(K+d_i^2\right)^2}{K+2d_i^2}$ [see Johnson and Kotz, 1970, p190]. Note that under the null hypothesis **H$_0$:** $d_A^2 = d_C^2$, we have $n_A = n_C = n$ and the approximate distribution is $F_{n\,n}$. We need an estimate of n. The *F* statistic in the regression has an expected value $F_i = \frac{(N-1-K)(K+d_i^2)}{K(N-3-K)}$ [see Johnson and Kotz, 1970, p.190]. Thus,

[26] We would like to thank Professor Gary Simon for suggesting and helping us develop it.

an estimate of d_i^2 is given by $\hat{d}_i^2 = \left[\frac{K(N-3-K)}{N-1-K}\right]F_i - K$ and hence an estimate of $\hat{n} = \frac{\left(K+\hat{d}\right)^2}{K+2\hat{d}}$,

with $\hat{d} = \left(\hat{d}_A^2 + \hat{d}_C^2\right)/2$.

Putting the derivations together, under the null hypothesis G is distributed $F_{\hat{n},\hat{n}} F_{N-1-K,N-1-K}$ with $\hat{n} = \frac{K+\hat{d}}{K+2\hat{d}}$, $\hat{d} = \left(\hat{d}_A^2 + \hat{d}_C^2\right)/2$, $\hat{d}_i^2 = \left[\frac{K(N-3-K)}{N-1-K}\right]F_i - K$.

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TABLE 1: Descriptive statistics

	Years 60 – 69					Years 70 - 79					Years 80 - 89				
	MV	**BV**	**NI**	**TA**	**R**	**MV**	**BV**	**NI**	**TA**	**R**	**MV**	**BV**	**NI**	**TA**	**R**
Mean	1118	540	64	923	1.17	876	653	83	1690	1.09	1194	859	106	3432	1.24
Standard Deviation	3132	1531	178	2533	0.28	2856	1990	263	5213	0.22	3310	2307	337	11244	0.32
Minimum	8	6	-4	8	0.79	2	1	-230	5	0.60	2	1	-949	4	0.64
First Quartile	108	69	7	121	1.02	52	55	5	119	0.96	85	64	5	145	1.06
Median	351	173	20	307	1.12	202	175	20	392	1.05	313	216	23	511	1.18
Third Quartile	846	427	47	818	1.25	658	609	71	1435	1.46	1083	820	95	2282	1.34
Maximum	32153	18621	1768	32277	3.59	39944	34001	3559	78385	2.47	62137	40458	5771	172313	4.10

Note: The table reports the average of the descriptive statistic over each 10-year period.

Variable Definitions: MV is the market value on the last trading day, three months subsequent to the fiscal year-end. TA is the total assets at the end of the fiscal year. BV is the book value at the end of the fiscal year and equals TA minus TL. TL is the total liabilities at the end of the fiscal year. NI is the net income earned during the fiscal year. R is the average annual return +1 for the last three years.

TABLE 1A: Preliminary tests of associations with a proxy for fundamental value

Panel A: Fundamental value using dividend flows for four years and fifth year's market value as terminal value

	MODEL A0 Dependent variable = FNDV(t)			MODEL B0 Dependent variable = FNDV(t)			MODEL C0 Dependent variable = FNDV(t)		
	60-69	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**
N	248	537	885	248	537	885	248	537	885
R^2	7.32	3.72	0.95	14.49	8.66	1.37	9.87	7.85	2.85
Adj. R^2	6.89	3.53	0.83	14.09	8.48	1.25	9.02	7.50	2.62
R^2 Ratio[f]	1.35	2.11	3.01	0.68	0.91	2.08			
(# of yrs >1)	(10)	(10)	(10)	(3)	(5)	(9)			
F-test							28.11	22.67	4.35
p-value							(0.00)	(0.01)	(0.19)
(# of yrs p-value < .01)							(7)	(6)	(3)

Panel B: Fundamental value using dividend flows for nine years and tenth year's market value as terminal value

	MODEL A0[a] Dependent variable = FNDV(t)			MODEL B0[b] Dependent variable = FNDV(t)			MODEL C0[c] Dependent variable = FNDV(t)		
	60-69	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**
N	244	503	596	244	503	596	244	503	596
R^2	1.36	0.70	0.27	1.79	1.69	0.50	3.10	2.91	2.78
Adj. R^2	0.90	0.49	0.05	1.59	1.23	0.28	2.19	2.52	2.35
R^2 Ratio[f]	2.27	4.19	10.15	1.73	1.72	2.08			
(# of yrs >1)	(10)	(10)	(10)	(7)	(7)	(10)			
F-test[g]							3.36	3.28	2.99
p-value							(0.21)	(0.24)	(0.28)
(# of yrs p-value < .01)							(2)	(1)	(0)

Notes to Table 1A:

a. Model A0: FNDV(t) = a_0 + a_2 NAPS + error. All variables are scaled with TA(t).

b. Model B0: FNDV(t) = b_0 + b_2 MV(t) + error. All variables are scaled with TA(t).

c. Model C0: FNDV(t) = c_0 + c_2 BV(t) + c_3 NI(t) + error. All variables are scaled with TA(t).

d. The coefficient estimates are the mean coefficient estimate computed from the yearly cross-sectional ordinary least square estimates.

e. The t-statistics of the coefficient estimate are the mean t-statistic computed from the yearly cross-sectional ordinary least square estimates.

f. The Ratios of Model C's mean R^2 to Model A's (B's) mean R^2 are obtained from the yearly cross-sectional regressions for each 10 year period. The parenthesis provides the number of years for which the ratios are greater than one.

g. The F-test is the mean of the partial F-test statistic computed from the yearly cross-sectional ordinary least square estimates, when MV(t) [or equivalently NAPS(t)] is added to Model C0

Variable Definitions: FNDV(t) = $\Sigma_{i=i,\ k}$ [DIV(t+i)/R(t)^j] + [MV(t+k+1) /R(t)$^{(k+1)}$] for k=4, 9. NAPS is computed by purging the book value and net income from stock price, comtemporaneously. MV is the market value on the last trading day, three months subsequent to the fiscal year-end. TA is the total assets at the end of the fiscal year. NI is the net income earned during the fiscal year. DIV is the dividends in period t. R is the average annual return +1 for the last three years.

TABLE 2: Levels - whole sample

Panel A: Dividends model

		MODEL A1[h] Dependent variable = NEPS			MODEL B1[i] Dependent variable = MV			MODEL C1[j] Dependent variable = NI		
		60-69	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**
	N	249	537	887	249	537	887	249	537	887
With Discounting[k]	**R^2**	13.69	9.69	5.66	59.51	45.56	24.15	70.50	52.95	37.03
	Adj. R^2	11.33	8.43	4.71	58.43	44.83	23.39	69.72	52.23	36.66
	R^2 Ratio[f]	5.15	5.47	5.86	1.18	1.16	1.37			
	(# of years ratio >1)	(10)	(10)	(10)	(10)	(10)	(10)			
	G-Stat.[g]	6.96	27.20	19.29						
	(# of years G-stat are significant)	(10)	(10)	(10)						
Without Discounting[m]	**R^2**	27.80	14.39	10.26	72.93	58.83	35.34	76.46	65.88	48.39
	Adj. R^2	25.84	13.24	9.30	72.22	58.27	34.91	74.82	65.43	47.88
	R^2 Ratio[f]	2.71	4.58	4.72	1.03	1.12	1.36			
	(# of years ratio >1)	(10)	(10)	(10)	(10)	(10)	(10)			
	G-Stat.[g] (# of years G-stat are significant)	9.32	15.77	14.64						
		(10)	(10)	(10)						

Panel B: Net Income model

		MODEL A2[h] Dependent variable = NEPS			MODEL B2[i] Dependent variable = MV			MODEL C2[j] Dependent variable = NI		
		60-69	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**
	N	249	537	887	249	537	887	249	537	887
With Discounting[k]	**R^2**	14.17	5.18	3.45	55.31	38.37	25.02	78.18	54.80	37.03
	Adj. R^2	12.18	4.26	2.89	54.33	37.77	24.59	77.71	54.36	36.66
	R^2 Ratio[f]	5.52	10.57	10.72	1.41	1.43	1.48			
	(# of years ratio >1)	(10)	(10)	(10)	(10)	(10)	(10)			
	G-Stat.[g] (# of years G-stat	25.86	24.64	57.03						
	are significant)	(10)	(10)	(10)						
Without Discounting[m]	**R^2**	31.45	18.88	14.16	70.49	57.60	45.66	82.29	67.48	56.30
	Adj. R^2	29.86	18.11	13.66	69.84	57.20	45.34	81.91	67.11	55.97
	R^2 Ratio[f]	2.61	3.57	3.97	1.17	1.17	1.23			
	(# of years ratio >1)	(10)	(10)	(10)	(9)	(9)	(10)			
	G-Stat.[g] (# of years G-stat are significant)	11.85	11.51	15.09						
		(10)	(10)	(10)						

Notes to Table 2:

a. Model A1: $NEPS(t) = a_0 + \Sigma_{i=i,4}\, a_i\, [DIV(t+i)/R(t)^i] + a_5\, [MV(t+5)\,/R(t)^5]$ + error. All variables are scaled with TA(t).

b. Model B1: $MV(t) = b_0 + \Sigma_{i=i,4}\, b_i\, [DIV(t+i)/R(t)^i] + b_5\, [MV(t+5)/R(t)^5]$ + error. All variables are scaled with TA(t).

c. Model C1: $NI(t) = c_0 + \Sigma_{i=i,4}\, c_i\, [DIV(t+i)/R(t)^i] + c_5\, [MV(t+5)\,/R(t)^5]$ + error. All variables are scaled with TA(t).

d. The coefficient estimates are the mean coefficient estimate computed from the yearly cross-sectional ordinary least square estimates.

e. The t-statistics of the coefficient estimate are the mean t-statistic computed from the yearly cross-sectional ordinary least square estimates.

f. The Ratios of Model C's mean R^2 to Model A's (B's) mean R^2 are obtained from the yearly cross-sectional regressions for each 10 year period. The parenthesis provides the number of years for which the ratios are greater than one.

g. The G-Statistic is the mean G-Statistic for the test for equality of the R^2 of Models A and C obtained from the yearly cross-sectional regressions (see Appendix B). The number in the parenthesis is the number of years for which the test statistic is significant at the one percent level.

h. Model A2: $NEPS(t) = a_0 + \Sigma_{i=i,4}\, a_i\, [NI(t+i)/R(t)^i] + a_5\, [\{MV(t+t+5) - FVNI(t+t+5)\}/R(t)^5]$ + error. All variables are scaled with TA(t).

i. Model B2: $MV(t) = b_0 + \Sigma_{i=i,4}\, b_i\, [NI(t+i)/R(t)^i] + b_5\, [\{MV(t+t+5) - FVNI(t+t+5)\}/R(t)^5]$ + error. All variables are scaled with TA(t).

j. Model C2: $NI(t) = c_0 + \Sigma_{i=i,4}\, c_i\, [NI(t+i)/R(t)^i] + c_5\, [\{MV(t+t+5) - FVNI(t+t+5)\}/R(t)^5]$ + error. All variables are scaled with TA(t).

k. For the model with discounting R(t) is the mean-annual return +1 computed over the past three years.

m. For the model without discounting R(t)=1.

Variable Definitions: NEPS for the dividend model is computed by purging the net income based information from the dividends and terminal value; and, NEPS in the earnings model is the market value adjusted for information content in earnings. MV is the market value on the last trading day, three months subsequent to the fiscal year-end. TA is the total assets at the end of the fiscal year. NI is the net income earned during the fiscal year. DIV is the dividends in period t. R is the average annual return +1 for the last three years.

TABLE 3: Partition based on firm size

Panel A: Small Size[f]

		MODEL A2[a] Dependent variable = NEPS			MODEL B2[b] Dependent variable = MV			MODEL C2[c] Dependent variable = NI		
		60-69	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**
	N	249	537	887	249	537	887	249	537	887
With Discounting[h]	**R^2**	8.44	4.98	2.80	51.08	30.05	16.57	73.85	47.58	32.44
	Adj. R^2	4.03	3.12	1.66	48.92	28.68	15.59	72.68	46.56	31.66
	R^2 Ratio[d]	8.75	9.55	11.59	1.45	1.58	1.96			
	(# of years ratio >1)	(10)	(10)	(10)	(10)	(10)	(10)			
	G-Stat.[e]	25.62	29.91	49.75						
	(# of years G-stat are significant)	(10)	(10)	(10)						
Without Discounting[i]	**R^2**	21.61	15.73	10.68	64.35	47.68	31.89	68.04	54.88	36.70
	Adj. R^2	17.82	14.09	9.63	62.78	46.66	31.09	67.04	54.00	35.97
	R^2 Ratio[d]	3.15	3.49	3.44	1.06	1.15	1.15			
	(# of years ratio >1)	(10)	(10)	(10)	(10)	(10)	(10)			
	G-Stat.[e]	13.13	13.13	13.13						
	(# of years G-stat are significant)	(10)	(10)	(10)						

Panel B: Large Size[g]

		MODEL A2[a] Dependent variable = NEPS			MODEL B2[b] Dependent variable = MV			MODEL C2[c] Dependent variable = NI		
		60-69	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**
	N	249	537	887	249	537	887	249	537	887
With Discounting[h]	**R^2**	27.79	8.42	5.78	71.40	55.44	43.75	84.61	66.75	52.04
	Adj. R^2	24.42	6.62	4.67	69.95	54.55	43.08	83.94	66.09	51.43
	R^2 Ratio[d]	3.04	7.93	9.01	1.19	1.20	1.19			
	(# of years ratio >1)	(10)	(10)	(10)	(10)	(10)	(10)			
	G-Stat.[e]	17.77	33.65	35.40						
	(# of years G-stat are significant)	(10)	(10)	(10)						
Without Discounting[i]	**R^2**	42.95	23.33	15.39	80.47	72.39	55.03	87.77	73.41	61.94
	Adj. R^2	40.28	21.86	14.40	79.57	71.85	54.51	87.23	72.89	61.49
	R^2 Ratio[d]	2.04	3.15	4.02	1.09	1.01	1.13			
	(# of years ratio >1)	(10)	(10)	(10)	(10)	(10)	(10)			
	G-Stat.[e]	4.12	7.59	9.40						
	(# of years G-stat are significant)	(10)	(10)	(10)						

Notes to Table 3:

a. Model A2: $NEPS(t) = a_0 + \Sigma_{i=i,4}\, a_i\, [NI(t+i)/R(t)^i] + a_5\, [\{MV(t+5) - FVNI(t+5)\}/R(t)^5]$ + error. All variables are scaled with TA(t).

b. Model B2: $MV(t) = b_0 + \Sigma_{i=i,4}\, b_i\, [NI(t+i)/R(t)^i] + b_5\, [\{MV(t+5) - FVNI(t+5)\}/R(t)^5]$ + error. All variables are scaled with TA(t).

c. Model C2: $NI(t) = c_0 + \Sigma_{i=i,4}\, c_i\, [NI(t+i)/R(t)^i] + c_5\, [\{MV(t+5) - FVNI(t+5)\}/R(t)^5]$ + error. All variables are scaled with TA(t).

d. The Ratios of Model C2's mean R^2 to Model A2's (B2's) mean R^2 are obtained from the yearly cross-sectional regressions for each 10-year period. The number of years for which the ratios are greater than one is provided in parenthesis.

e. The G-Statistic (derived in Appendix C to test for equality of the R^2 of Models A2 and C2) is the mean G-Statistic obtained from the yearly cross-sectional regressions. The number of years for which the test statistic is significant at the 1% level is provided in parenthesis.

f. Small size firms are firms that are below the median market value, classified each year.

g. Large size firms are firms that are above the median market value, classified each year.

h. For the model with discounting R(t) is the mean-annual return computed over the past three years.

i. For the model without discounting R(t)=1.

Variable Definitions: NEPS is the market value adjusted for information content in earnings. MV is the market value on the last trading day, three months subsequent to the fiscal year-end. TA is the total assets at the end of the fiscal year. NI is the net income earned during the fiscal year. R is the average annual return for the last three years.

TABLE 4: Partition based on book-to-market – earnings model

Panel A: Small book-to-market ratio[f] [high growth]

		MODEL A2[a] Dependent variable = NEPS			MODEL B2[b] Dependent variable = MV			MODEL C2[c] Dependent variable = NI		
		60-69	70-79	80-89	60-69	70-79	80-89	60-69	70-79	80-89
	N	123	267	442	123	267	442	123	267	442
With Discounting[h]	R^2	19.29	8.21	4.01	52.37	35.59	26.41	80.04	56.50	44.45
	Adj. R^2	15.39	6.40	2.88	50.14	34.31	25.54	79.17	55.63	43.74
	R^2 Ratio[d]	4.15	6.88	11.09	1.53	1.59	1.68			
	(# of years ratio >1)	(10)	(10)	(10)	(10)	(10)	(10)			
	G-Stat.[e]	21.65	18.95	25.23						
	(# of years G-stat are significant)	(10)	(10)	(10)						
Without Discounting[i]	R^2	32.37	19.24	12.12	64.73	51.15	41.19	76.90	61.26	51.00
	Adj. R^2	29.13	17.68	11.08	63.09	50.21	40.49	76.18	60.51	50.35
	R^2 Ratio[d]	2.38	3.18	4.21	1.19	1.20	1.24			
	(# of years ratio >1)	(10)	(10)	(10)	(10)	(10)	(10)			
	G-Stat.[e]	6.39	10.67	13.13						
	(# of years G-stat are significant)	(10)	(10)	(10)						

Panel B: Large book-to-market ratio[g] [low growth]

		MODEL A2[a] Dependent variable = NEPS			MODEL B2[b] Dependent variable = MV			MODEL C2[c] Dependent variable = NI		
		60-69	70-79	80-89	60-69	70-79	80-89	60-69	70-79	80-89
	N	124	268	442	124	268	442	124	268	442
With Discounting[h]	R^2	13.52	6.59	4.60	46.66	25.19	10.11	62.95	36.89	27.16
	Adj. R^2	9.03	4.76	3.50	44.11	23.72	9.06	61.18	35.65	26.31
	R^2 Ratio[d]	4.65	5.59	5.90	1.35	1.46	2.69			
	(# of years ratio >1)	(10)	(10)	(10)	(10)	(10)	(10)			
	G-Stat.[e]	8.91	9.84	7.79						
	(# of years G-stat are significant)	(10)	(10)	(10)						
Without Discounting[i]	R^2	19.55	10.68	6.34	51.54	36.02	18.80	66.00	42.91	27.72
	Adj. R^2	15.05	8.93	5.30	49.16	34.78	17.84	64.34	41.79	26.88
	R^2 Ratio[d]	3.38	4.02	4.37	1.28	1.19	1.47			
	(# of years ratio >1)	(10)	(10)	(10)	(9)	(9)	(10)			
	G-Stat.[e]	29.40	7.40	14.12						
	(# of years G-stat are significant)	(10)	(10)	(10)						

Notes to Table 4:

a. Model A2: $NEPS(t) = a_0 + \Sigma_{i=i,4}\, a_i\, [NI(t+i)/R(t)^i] + a_5\, [\{MV(t+5) – FVNI(t+5)\}/R(t)^5]$ + error. All variables are scaled with TA(t).

b. Model B2: $MV(t) = b_0 + \Sigma_{i=i,4}\, b_i\, [NI(t+i)/R(t)^i] + b_5\, [\{MV(t+5) – FVNI(t+5)\}/R(t)^5]$ + error. All variables are scaled with TA(t).

c. Model C2: $NI(t) = c_0 + \Sigma_{i=i,4}\, c_i\, [NI(t+i)/R(t)^i] + c_5\, [\{MV(t+5) – FVNI(t+5)\}/R(t)^5]$ + error. All variables are scaled with TA(t).

d. The Ratios of Model C2's mean R^2 to Model A2's (B2's) mean R^2 are obtained from the yearly cross-sectional regressions for each 10-year period. The number of years for which the ratios are greater than one is provided in parenthesis.

e. The G-Statistic (derived in Appendix B to test for equality of the R^2 of Models A2 and C2) is the mean G-Statistic obtained from the yearly cross-sectional regressions. The number of years for which the test statistic is significant at the 1% level is provided in parenthesis.

f. Small book-to-market firms are firms that are below the median book-to-market ratio, classified each year.

g. Large book-to-market firms are firms that are above the median book-to-market ratio, classified each year.

h. For the model with discounting R(t) is the mean-annual return computed over the past three years.

i. For the model without discounting R(t)=1.

Variable Definitions: NEPS is the market value adjusted for information content in earnings. MV is the market value on the last trading day, three months subsequent to the fiscal year-end. TA is the total assets at the end of the fiscal year. NI is the net income earned during the fiscal year. R is the average annual return for the last three years

TABLE 5: Partition based on industry classification

Panel A: Sum of firms' NI and MV by two digit industry groups

		MODEL A2[a] Dependent variable = NEPS			MODEL B2[b] Dependent variable = MV			MODEL C2[c] Dependent variable = NI		
		60-69	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**
	N	97	160	198	97	160	198	97	160	198
With Discounting[h]	**R^2**	41.99	24.11	19.47	88.26	79.16	68.22	97.43	92.22	81.07
	Adj. R^2	38.72	21.59	17.36	87.63	78.45	67.39	97.30	91.96	80.57
	R^2 Ratio[d]	2.32	3.82	4.16	1.10	1.16	1.19			
	(# of years ratio >1)	(10)	(10)	(10)	(10)	(10)	(10)			
	G-Stat.[e]	65.84	67.38	27.01						
	(# of years G-stat are significant)	(10)	(10)	(10)						
Without Discounting[i]	**R^2**	62.47	55.14	45.76	93.63	88.85	84.69	98.32	94.20	90.49
	Adj. R^2	60.30	53.36	44.34	93.28	88.48	84.29	98.23	94.01	89.36
	R^2 Ratio[d]	1.57	1.71	1.98	1.05	1.06	1.07			
	(# of years ratio >1)	(10)	(10)	(10)	(10)	(10)	(10)			
	G-Stat.[e]	8.23	21.96	39.42						
	(# of years G-stat are significant)	(10)	(10)	(10)						

Panel B: Firms' in non-intangible intensive industries[h]

		MODEL A2[a] Dependent variable = NEPS			MODEL B2[b] Dependent variable = MV			MODEL C2[c] Dependent variable = NI		
		60-69	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**
	N	222	485	783	222	485	783	222	485	783
With Discounting[h]	**R^2**	12.36	4.77	3.30	55.72	38.45	25.61	77.08	55.01	37.11
	Adj. R^2	10.07	3.75	2.67	54.49	37.77	25.12	76.53	54.53	36.70
	R^2 Ratio[d]	6.24	11.52	11.25	1.38	1.43	1.45			
	(# of years ratio >1)	(10)	(10)	(10)	(10)	(10)	(10)			
	G-Stat.[e]	27.97	22.49	60.27						
	(# of years G-stat are significant)	(10)	(10)	(10)						
Without Discounting[i]	**R^2**	25.45	17.08	13.94	65.01	56.29	45.82	80.82	72.76	63.67
	Adj. R^2	23.51	16.21	13.37	64.15	55.83	45.46	80.35	72.36	63.30
	R^2 Ratio[d]	3.18	4.26	4.57	1.24	1.29	1.39			
	(# of years ratio >1)	(10)	(10)	(10)	(10)	(10)	(10)			
	G-Stat.[e]	5.40	12.64	18.52						
	(# of years G-stat are significant)	(10)	(10)	(10)						

Panel C: Firms' in intangible intensive industries[h]

		MODEL A2[a] Dependent variable = NEPS			MODEL B2[b] Dependent variable = MV			MODEL C2[c] Dependent variable = NI		
		60-69	70-79	80-89	60-69	70-79	80-89	60-69	70-79	80-89
	N	27	52	104	27	52	104	27	52	104
With Discounting[h]	R^2	25.05	11.56	6.76	76.97	48.48	31.92	87.32	61.99	45.13
	Adj. R^2	4.84	1.49	1.53	71.62	42.52	28.18	84.56	57.67	42.10
	R^2 Ratio[d]	3.49	5.37	6.68	1.13	1.28	1.41			
	(# of years ratio >1)	(10)	(10)	(10)	(10)	(10)	(10)			
	G-Stat.[e]	17.67	19.03	44.08						
	(# of years G-stat are significant)	(10)	(10)	(10)						
Without Discounting[i]	R^2	39.25	30.02	16.24	86.21	68.68	49.60	90.67	69.75	52.63
	Adj. R^2	22.12	22.22	11.45	82.77	65.27	46.79	88.53	66.27	49.79
	R^2 Ratio[d]	2.31	2.32	3.24	1.05	1.02	1.06			
	(# of years ratio >1)	(10)	(10)	(10)	(8)	(7)	(9)			
	G-Stat.[e]	7.18	10.24	30.09						
	(# of years G-stat are significant)	(10)	(10)	(10)						

Notes to Table 5:

a. Model A2: $NEPS(t) = a_0 + \Sigma_{i=i,4}\, a_i\, [NI(t+i)/R(t)^i] + a_5\, [\{MV(t+5) – FVNI(t+5)\}/R(t)^5]$ + error. All variables are scaled with TA(t).

b. Model B2: $MV(t) = b_0 + \Sigma_{i=i,4}\, b_i\, [NI(t+i)/R(t)^i] + b_5\, [\{MV(t+5) – FVNI(t+5)\}/R(t)^5]$ + error. All variables are scaled with TA(t).

c. Model C2: $NI(t) = c_0 + \Sigma_{i=i,4}\, c_i\, [NI(t+i)/R(t)^i] + c_5\, [\{MV(t+5) – FVNI(t+5)\}/R(t)^5]$ + error. All variables are scaled with TA(t).

d. The Ratios of Model C2's mean R^2 to Model A2's (B2's) mean R^2 are obtained from the yearly cross-sectional regressions for each 10-year period. The number of years for which the ratios are greater than one is provided in parenthesis.

e. The G-Statistic (derived in Appendix B to test for equality of the R^2 of Models A2 and C2) is the mean G-Statistic obtained fromthe yearly cross-sectional regressions. The number of years for which the test statistic is significant at the 1% level is provided in parenthesis.

f. Firms operating in SIC codes 282, 283, 357, 367, 48, 73 and 87 are categorized as intangible intensive industries.

h. For the model with discounting R(t) is the mean-annual return computed over the past three years.

i. For the model without discounting R(t)=1.

Variable Definitions: NEPS is the market value adjusted for information content in earnings. MV is the market value on the last trading day, three months subsequent to the fiscal year-end. TA is the total assets at the end of the fiscal year. NI is the net income earned during the fiscal year. R is the average annual return for the last three years.

TABLE 6: Sensitivity tests

Panel A: First difference model[a]

		MODEL A2 Dependent variable = NEPS(t)			MODEL B2 Dependent variable = MV(t)			MODEL C2 Dependent variable = NI(t)		
		60-69	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**
	N	249	537	887	249	537	887	249	537	887
With Discounting[e]	**R^2**	6.68	4.59	1.88	12.85	5.32	3.13	6.74	8.22	10.70
	Adj. R^2	4.49	3.66	1.31	10.81	4.41	2.57	4.57	7.33	10.18
	R^2 Ratio[c]	1.01	1.79	5.69	0.52	1.54	3.42			
	(# of years ratio >1)	(6)	(6)	(7)	(2)	(6)	(7)			
	G-Stat.[d]	2.42	4.27	23.25						
	(# of years G-stat are significant)	(t+5)	(7)	(8)						
Without Discounting[f]	**R^2**	8.08	6.67	2.61	16.84	7.92	4.36	8.27	8.36	9.64
	Adj. R^2	5.91	5.76	2.05	14.86	7.03	3.80	6.11	7.48	9.11
	R^2 Ratio[c]	1.02	1.25	3.69	0.49	1.06	2.21			
	(# of years ratio >1)	(6)	(7)	(8)	(2)	(6)	(7)			
	G-Stat.[d]	3.71	2.51	13.77						
	(# of years G-stat are significant)	(4)	(6)	(8)						

Panel B: Cash flow based model[b]

		MODEL A2 Dependent variable = NEPS(t)			MODEL B2 Dependent variable = MV(t)			MODEL C2 Dependent variable = NI(t)		
		60-69	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**	**60-69**	**70-79**	**80-89**
	N	227	482	715	227	482	715	227	482	715
With Discounting[e]	**R^2**	6.27	2.67	2.52	30.18	17.38	9.60	34.93	21.32	18.98
	Adj. R^2	3.87	1.63	1.82	28.42	16.49	8.95	33.34	20.47	18.40
	R^2 Ratio[c]	5.57	7.99	7.53	1.16	1.23	1.98			
	(# of years ratio >1)	(10)	(10)	(10)	(6)	(6)	(7)			
	G-Stat.[d]	13.04	11.51	23.98						
	(# of years G-stat are significant)	(10)	(10)	(10)						
Without Discounting[f]	**R^2**	21.54	15.40	11.34	52.32	41.63	28.17	62.71	49.83	36.78
	Adj. R^2	20.56	11.30	10.71	51.20	41.01	27.66	61.82	49.30	36.33
	R^2 Ratio[c]	2.91	3.24	3.24	1.20	1.20	1.31			
	(# of years ratio >1)	(10)	(10)	(10)	(7)	(7)	(8)			
	G-Stat.[d]	5.57	6.44	7.59						
	(# of years G-stat are significant)	(10)	(10)	(10)						

Notes to Table 6:

a. For Models A2, B2 and C2 the dependent and independent variables in levels are replaced with the first differences [{NI(t+n) – NI(t+n-1)}/{R^n*TA(t+n)}] and [{MV(t+n) – MV(t+n-1)}/{R^n*TA(t+n)}]. All variables are scaled by TA(t).

b. For Models A2, B2 and C2, the independent variables in net income levels are replaced with the free cash flows CF(t+n). All variables are scaled with TA.

c. The Ratios of Model C's mean R^2 to Model A's (B's) mean R^2 obtained from the yearly cross-sectional regressions. The number of years the ratios are greater than one is provided in parenthesis.

d. The G-Statistic (derived in Appendix C to test for equality of the R^2 of Models A2 and C2) is the mean G-Statistic obtained from the yearly cross-sectional regressions. The number of years for which the test statistic is significant at the 1% level is provided in parenthesis.

e. For the model with discounting R(t) is the mean-annual return computed over the past three years.

f. For the model without discounting R(t)=1.

Variable definitions: CF(t) is the estimate of free cash flows computed as net income in period t adjusted for the change in current assets (CA) and current liabilities (CL), i.e., CF(t) = NI(t) + [CL(t) – CL(t-1)] – [CA(t) – CA(t-1)]. All other variable definitions are the same as in the previous tables. NEPS(t) for the first differences were computed in the same fashion as in previous tables. NEPS(t) for the cash flow based model is computed by purging the net income based information from the cash flows and terminal value;.

TABLE 7: Descriptive statistics of explanatory and control variables

Panel A: Descriptive statistics of explanatory and control variables

Variables	Mean	Standard Deviation	Minimum	1st Quartile	Median	3rd Quartile	Maximum
MVOL	31.32	37.11	1.32	2.96	14.03	56.10	132.05
LNMVOL	2.55	1.49	0.28	1.08	2.64	4.02	4.88
MLOSS	0.04	0.04	0.00	0.01	0.02	0.07	0.12
MONETIME	0.29	0.11	0.13	0.23	0.26	0.38	0.51
MINTANG	0.11	0.02	0.09	0.10	0.10	0.11	0.15

Panel B: Correlation between R^2 and explanatory and control variables

	R^2(Model A2)	R^2(Model B2)
LNMVOL	-0.77*	-0.82*
MLOSS	-0.58*	-0.73*
MONETIME	-0.45**	-0.62*
MINTANG	0.12	0.03
YEAR	-0.76*	-0.82*

Panel C: Correlation among explanatory and control variables

	LNMVOL	MLOSS	MONETIME	MINTANG
MLOSS	0.86*			
MONETIME	0.82**	0.90*		
MINTANG	0.15	0.25	0.45**	
YEAR	0.99*	0.87*	0.80*	0.16

Variable definitions: VOL is the trading volume during the fiscal year divided by the number of common shares outstanding at the end of the fiscal year. MVOL is the mean of VOL each year. LNMVOL is the log of MVOL. MLOSS is the percentage of firms each year whose operating income is negative. MONETIME is the percentage of firms each year who have special and/or extraordinary items. MINTANG is the percentage of firms each year who are in SIC codes 282, 283, 357, 367, 48, 73 and 87.

TABLE 8: Trading volume and predictive ability of prices

	Dependent variable = R^2				Dependent variable = R^2			
	Model A2		Model B2		Model A2		Model B2	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Intercept	0.15	11.08*	0.60	18.84*	0.07	1.63	0.42	3.68*
LNMVOL	-0.03	-6.36*	-0.08	-7.48*	-0.04	-4.70*	-0.07	-3.21*
MLOSS					-0.04	-0.08	-0.81	-0.71
MONETIME					0.22	1.26	0.15	0.35
MINTANG					0.42	0.84	1.41	1.10
R^2	59.12		66.69		68.88		70.14	
Adj. R^2	57.66		65.50		63.91		65.36	
N	30		30		30		30	

Variable definitions: VOL is the trading volume during the fiscal year divided by the number of common shares outstanding at the end of the fiscal year. MVOL is the mean of VOL each year. LNMVOL is the log of MVOL. MLOSS is the percentage of firms each year whose operating income is negative. MONETIME is the percentage of firms each year who have special and/or extraordinary items. MINTANG is the percentage of firms each year who are in SIC codes 282, 283, 357, 367, 48, 73 and 87.

Figure 1: R^2 of the Models over the period 1960 to 1989

Figure 1a: R-square of Model A2 over time

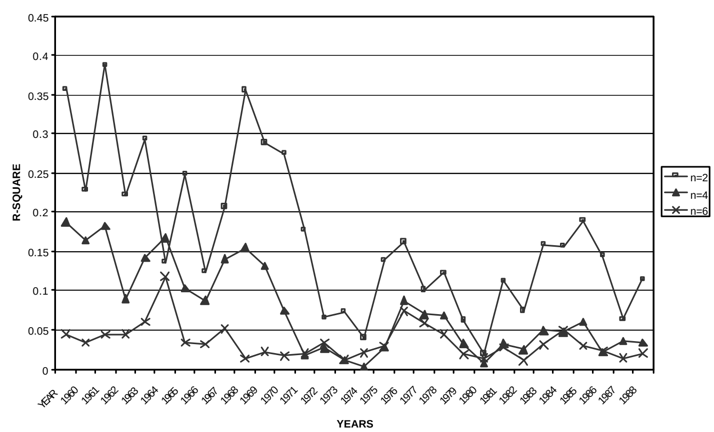


Figure 1b: R-square of Model B2 over time

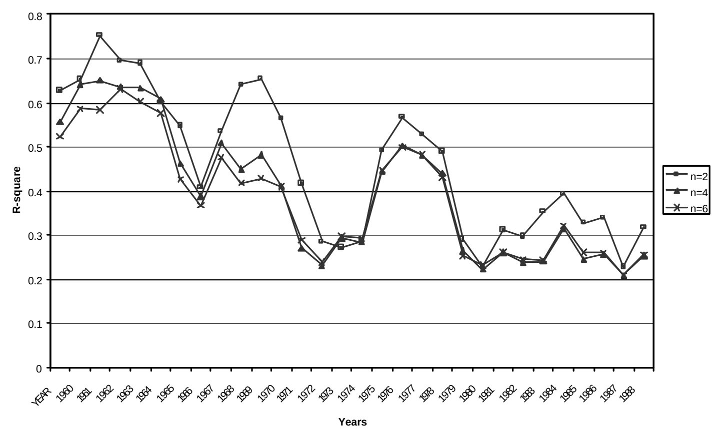
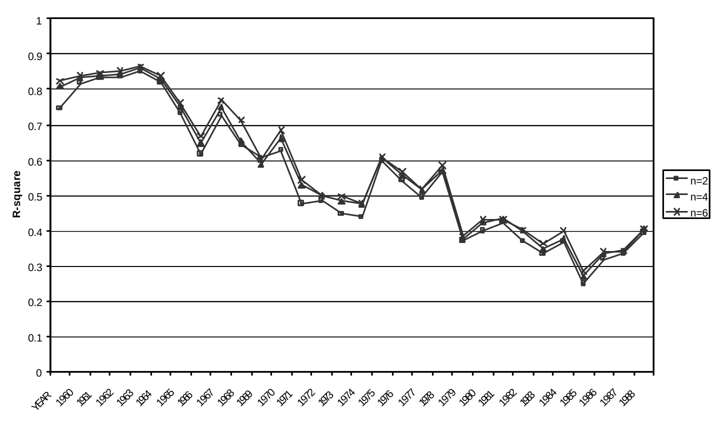


Figure 1c: R -square of Model C2 over time



Notes to Figure 1:

Model A2: $NEPS(t) = a_0 + \Sigma_{i=i,n} a_i [NI(t+i)/R(t)^i] + a_5 [\{MV(t+n+1) - FVNI(t+n+1)\}/R(t)^6]$ + error, for n=2,4,6.

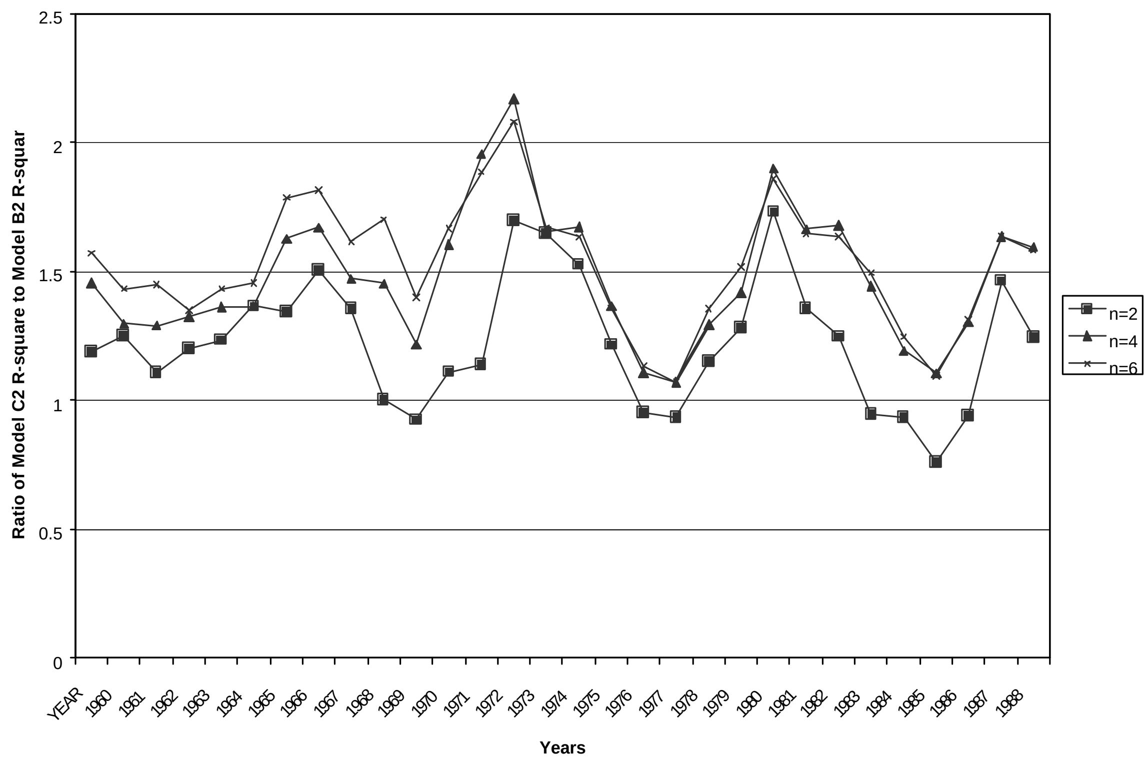
Model B2: $MV(t) = b_0 + \Sigma_{i=i,n} b_i [NI(t+i)/R(t)^i] + b_5 [\{MV(t+n+1) - FVNI(t+n+1)\}/R(t)^6]$ + error, for n=2,4,6.

Model C2: $NI(t) = c_0 + \Sigma_{i=i,n} c_i [NI(t+i)/R(t)^i] + c_5 [\{MV(t+n+1) - FVNI(t+n+1)\}/R(t)^6]$ + error, for n=2,4,6.

All variables are scaled with TA(t).

Variable Definitions: NEPS is the market value adjusted for information content in earnings. MV is the market value on the last trading day, three months subsequent to the fiscal year-end. TA is the total assets at the end of the fiscal year. NI is the net income earned during the fiscal year. R is the average annual return for the last three years

Figure 2: Relative predictive power of net income and stock price



Notes to Figure 2:

Model B2: $MV(t) = b_0 + \Sigma_{i=i,n}\, b_i\, [NI(t+i)/R(t)^i] + b_5\, [\{MV(t+n+1) - FVNI(t+n+1)\}/R(t)^6]$ + error, for n=2,4,6.

Model C2: $NI(t) = c_0 + \Sigma_{i=i,n}\, c_i\, [NI(t+i)/R(t)^i] + c_5\, [\{MV(t+n+1) - FVNI(t+n+1)\}/R(t)^6]$ + error, for n=2,4,6.

All variables are scaled with TA(t).

Variable Definitions: NEPS is the market value adjusted for information content in earnings. MV is the market value on the last trading day, three months subsequent to the fiscal year-end. TA is the total assets at the end of the fiscal year. NI is the net income earned during the fiscal year. R is the average annual return for the last three years

[1]