ESSAYS ON EARNINGS RESPONSE COEFFICIENT

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ABSTRACT

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The first essay examines the impact of existence/nonexistence of a unit root in earnings on (1) the magnitude of earnings persistence, and (2) on the association between earnings persistence and the earnings response coefficient. An analysis of the time-series properties of earnings suggest that the existence of a unit root (i.e., the existence of a stochastic nonstationary component) in earnings is applicable for only a small sub-set of firms. Two measures of earnings persistence and earnings innovations are computed—one assuming a difference stationary model and the other assuming a level stationary model. The results indicate that the identification of the existence or lack of a unit root in earnings significantly improves the association between earnings persistence and the earnings response coefficient. The strength of the price-earnings regression is positively related to the probability of a unit root in earnings. For the difference stationary model, the predictability of earnings confounds the effects of nonstationarity of earnings as a determinant of the earnings response coefficient.

The second essay argues that measurement error in unexpected earnings (value-relevant transitory components as well as value-irrelevant noise) significantly contributes to the bias and inter-temporal instability in the earnings response coefficients. The monotonic decrease in the cross-sectional earnings response coefficient documented in prior

work is driven by shifts in the variability of unexpected earnings that is unrelated to stock price movements. As predicted, the empirical analysis (using both actual and simulated data) suggests that this evidence is consistent with the measurement error argument. Furthermore, the results indicate that the role of measurement error is independent of the lead-lag relation between price and earnings.

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Chapter One

INTRODUCTION AND OVERVIEW

1.1 INTRODUCTION

Contemporary accounting research provides strong evidence in support of the information content of reported earnings (Ball and Brown [1968], Beaver [1968], Beaver, Clarke, and Wright [1979], Patell and Wolfson [1979, 1984], Beaver, Lambert, and Morse [1980], etc.). Recent studies investigate the nature of information in reported earnings and how this information relates to firm value. Specifically, Kormendi and Lipe [1987] focus on how the magnitude of the earnings response coefficient relates to the time-series properties of earnings. Based on Miller and Rock's [1985] model, Kormendi and Lipe provide evidence that the earnings response coefficient is a function of "earnings persistence."

Both Kormendi and Lipe [1987] and Lipe [1986] implicitly assume the existence of a unit root (or a permanent component in earnings) in earnings series in fitting a time-series model and in estimating earnings persistence and earnings innovations. The assumption of a unit root, even lacking a theoretical justification, has far reaching implications for valuation theory.[1] A unit root in earnings implies a stochastic

[1]For some economic variables the presence of a unit root is a theoretical implication of models which postulate rational use of information available to economic agents (e.g., Samuelson [1973], Meese and Singleton [1982]). There is no such theoretical implication for the time series properties of earnings (see Lorek Kee and Vass [1981, p. 106]), i.e., rational expectations does not imply a unit root in earnings. Jensen [1970] indicates "while one might argue that competition in product and factor markets might cause firm income levels to behave as a random walk I do not find these arguments as forceful as those applied to security prices where transaction costs are extremely low and there are no 'fixed factors' inhibiting movement of funds." This does not preclude the possibility of earnings exhibiting a random walk process consistent

nonstationary component. The presence of a stochastic nonstationary component yields random shocks in earnings that have an enduring effect on future earnings (i.e., it implies a permanent component in earnings). The lack of a stochastic nonstationary component yields random shocks having a dissipating effect. Watts and Zimmerman [1986] emphasize that "[r]andom walk models have very different implications for the relation between earnings and stock prices ..." (p. 143). Therefore, a significant determinant of the earnings response coefficient ("persistence") is the existence/nonexistence of a stochastic nonstationarity component (unit root) in earnings.

In the first essay, I extend the work of Kormendi and Lipe by investigating the impact of a unit root in earnings on (1) the magnitude of earnings persistence, and (2) the association between earnings persistence and the earnings response coefficient. Descriptive evidence on the time-series properties of earnings suggest that the assumption of a difference stationary model (permanent component) for earnings is appropriate only for a sub-set of firms. A recently developed econometric method is used to test for the existence of a unit root in earnings (see Phillips [1987]). Identification of the existence (or nonexistence) of a unit root in earnings significantly improves the association between earnings persistence and the earnings response coefficient. Additional analysis suggests that the strength of the price-earnings regression is positively related to the probability of a unit root in earnings. Thus, testing for a unit root in earnings is useful in understanding the magnitude and the strength of the price-earnings relation.

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with a random walk process for prices (see Kleidon [1986, p. 979]).

Although the role of earnings in security valuation has been the most researched area in empirical financial accounting, there is growing concern among researchers that price-earnings studies provide us a very limited understanding of the price-earnings relation, and have no practical usefulness in predicting future stock returns. Specifically, the low R^2 of the price-earnings regressions, combined with inter-temporal instability in the earnings response coefficients (ERC), suggests that earnings have limited usefulness to investors. In a recent study, Lev [1989] echoes this sentiment: "The degree of intertemporal stability of returns/earnings relation is ... an important determinant of the usefulness of earnings to investors. However, researchers have paid scant attention to this issue."

In the second essay, I argue that a significant portion of the intertemporal instability in ERCs is driven by temporally dependent measurement error (e.g., value relevant transitory earnings, pure noise) in unexpected earnings. Once the measurement error is diversified across samples, I document dramatic improvement in the <u>stability</u> of the cross-sectional ERC estimates. Similarly, once I control for the level of measurement error, the <u>magnitude</u> of the cross-sectional ERC estimate increases nine-fold. Thus, the results of this essay highlight the importance of controlling measurement error in understanding the price-earnings relation.

1.2 OVERVIEW OF THE FIRST ESSAY

Within Kormendi and Lipe's [1987] framework, I demonstrate that the magnitude of earnings persistence depends on the existence/nonexistence of a unit root in earnings. I also show that an upward bias (as observed by

Kormendi and Lipe) in estimates of earnings persistence could be a natural product of overdifferencing the earnings series. I develop two sets of earnings persistence and earnings response coefficients—one assuming a difference stationary model for earnings (i.e., a unit root) and the other a stationary model in level earnings. To provide evidence on the effects of nonstationarity on the association between earnings persistence and the earnings response coefficient, I measure the probability of a unit root (using the unit root test statistic as a proxy) for each firm's earnings using recently developed econometric techniques (Phillips [1987], Phillips and Perron [1986], and Perron [1986a, 1986b]). Based on this measure, I assign firms to four different groups, where firms in Group 1 (4) have the highest (lowest) probability of a unit root.

I test three hypotheses on the association between earnings persistence and the earnings response coefficient conditional on earnings nonstationarity. First, since the firms in Group 1 have the highest probability of a unit root, I expect the difference stationary model to be the more appropriate of the two time series models. Thus, I hypothesize that the correlation between earnings persistence and the earnings response coefficient from the difference stationary model to be monotonically decreasing from Group 1 to Group 4. Second, I predict the opposite behavior for the level stationary model. Finally, I hypothesize that the difference (level) stationary model will be more descriptively valid for Group 1 (Group 4) as measured by the strength of association between earnings persistence and the earnings response coefficient.

The results are based on a sample of 449 firms. The autoregressive coefficient estimates from the two time series models suggest that a difference stationary model applied to earnings of all firms may lead to overdifferencing of the earnings series. For the difference stationary model, there is strong evidence of upward bias in earnings persistence compared with the earnings response coefficient, consistent with Kormendi and Lipe [1987]. For the level stationary model, the upward bias is less pronounced suggesting that, on average, earnings are better described by this model. The use of a level stationary model also yields a stronger (in a statistical sense) price-earnings relation.

The results also provide evidence of a significant association between earnings persistence and the earnings response coefficient for both time series models. Furthermore, correlation analysis between two sets of earnings persistence and earnings response coefficients suggests that the choice of time series model has a larger impact on the measurement of earnings persistence relative to the earnings response coefficient. Overall, the results provide evidence consistent with all three hypotheses. The strong association obtained between earnings persistence and the earnings response coefficient in the difference stationary model is primarily driven by those firms with the highest probability of a unit root. For the level stationary model, a significant association is evident in three of the four groups. With the exception of Group 4, the results for the level stationary model are consistent with the predictions. The results also indicate that the difference (level) stationary model performs better for the group with the highest (lowest) probability of a unit root. Thus, the evidence indicates that the assumption of a unit root in earnings is not descriptively valid for a majority of the firms sampled.

These results are also related to the growing literature on the excess volatility of stock prices (see Kormendi and Lipe [1987, p. 325]).

For example, if the observed earnings response coefficients are greater than the earnings persistence, then it could be argued that stock prices are excessively sensitive to earnings innovations. Even though there is no evidence of excess volatility in stock prices based on the regression results of both time series models, the difference stationary model is more biased towards rejecting the excess volatility hypothesis.

The evidence indicates that the probability of a negative earnings response coefficient is inversely related to the probability of a unit root in earnings. This is consistent with the measurement error in the earnings response coefficient monotonically increasing with the probability of a unit root. To control for the impact of measurement error on the association between earnings persistence and the earnings response coefficient, the correlation analysis is replicated for firms with positive earnings response coefficients. The results indicate a stronger association between earnings persistence and the earnings response coefficient for most groups and provide stronger evidence consistent with my three primary hypotheses.

To control for any measurement error in earnings persistence, the probability of a unit root is considered as an independent variable in a multiple regression model to explain the variability in the earnings response coefficient. Specifically, an interaction term between earnings persistence and the probability of a unit root is included as an independent variable since the bias in earnings persistence is a function of the probability of a unit root. Its inclusion results in a marked improvement in the explanatory power of the model for both the difference and level stationary models. This model explains about 50% of the variability in the earnings response coefficient. Furthermore, the greatest increase in R^2 occurs for the group with the highest probability of a unit root. This is to be expected since the largest change in earnings persistence occurs between a unit root and a near unit root series.

An analysis of statistics from price-earnings regressions indicates a strong positive association between the strength of the price-earnings regression and the probability of a unit root in earnings. The results also indicate that the level stationary model outperforms the difference stationary model in terms of the strength of price-earnings association. This evidence holds for all groups of firms. I also compare the level and difference stationary models with the random walk model. These results indicate that the random walk model outperforms (is outperformed by) the difference (level) stationary model in terms of the strength of the price-earnings relation. Thus, the assumption of a unit root in earnings for all firms, as evidenced by use of either a random walk model or a more complicated difference stationary model, is inappropriate for price-earnings regressions.

Finally, since it is reasonable to expect more persistent earnings to be more predictable, I consider the possibility that the effects of nonstationarity in earnings could be driven by cross-sectional differences in predictability. To test this, I group firms by the magnitude of earnings predictability (defined by the coefficient of variation of earnings innovation). I then replicate the analysis separately on groups conditional on earnings predictability. For the difference stationary model, I find that the significant association between earnings persistence and the earnings response coefficient is driven by firms with the highest probability of a unit root <u>and</u> the highest earnings predictability. For the level stationary model, I find that earnings predictability is not confounding the role of nonstationarity as a determinant of the price-earnings relation.

1.3 OVERVIEW OF THE SECOND ESSAY

Assuming a linear relation between earnings and stock returns, this essay provides a theoretical definition for the expected value of the "cross-sectional ERC" in three stages.[2] In the first stage, assuming error-free unexpected earnings, I show that the expected value is equal to the weighted average of the firm-specific ERCs with weights being the squared unexpected earnings of the estimation period. This suggests that the extant methodology induces inter-temporal variation in the cross-sectional ERC independent of differences in sample firms' ERCs. In the second stage, I derive the expected value of the "cross-sectional ERC" after introducing measurement error in unexpected earnings. I show that the cross-sectional ERC is downward biased and this bias is a function of the cross-sectional noise to signal ratio. In the third stage, I examine the role of a distinct value relevant transitory element in addition to pure measurement error in deriving the expected value of the cross-sectional response coefficient. I show that the effect of a value relevant transitory element is similar to that of noise in biasing the ERC estimate downward. Throughout the essay, the term measurement error is used in a generic sense to include both noise and value relevant

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[2]Kormendi and Lipe [1987] provide a theoretical model predicting both a linear relation and the expected magnitude of association between stock returns and unexpected earnings at the firm-specific level.

transitory elements in earnings.

The empirical analysis is conducted based on a sample of 679 December fiscal-year firms for the period 1968–1987. Consistent with prior work (Rayburn [1986] and Lev [1989]), both the annual ERC estimates and the R^2 of the price-earnings regression exhibit considerable instability over the sample period. The Chow tests of pair-wise ERCs reject the null hypothesis of intertemporal stability about half the time. This instability is due to the temporal changes in the two components of the theoretical ERC. The two components of the theoretical annual ERCs (i.e., the firm-specific ERCs and the magnitude of the unexpected earnings in the estimation period) explain more than 60% of the variability of the annual ERC estimates.

Within a measurement error framework, I predict a positive (negative) cross-sectional association between the ERC estimate and the variance of the observed unexpected earnings, if the variance of the observed unexpected earnings is primarily determined by the variance of the "true" unexpected earnings (the variance of the measurement error). The empirical analysis using both actual and simulated data suggests that the observed negative association between the ERC estimate and the variance of observed unexpected earnings is consistent with the measurement error argument both under the constant and varying persistence scenarios. In addition, if increases in the variance of unexpected earnings variance proxy for "true" signal, then one should observe corresponding increases in the covariation between returns and unexpected earnings. The empirical evidence indicates that the magnitude of both the annual and firm-specific ERC estimates are primarily driven by the variance of the observed unexpected earnings (the denominator) and not by the covariance between the stock return and the unexpected earnings (the numerator). These results suggest that a significant portion of the variance shifts in unexpected earnings are driven by measurement error rather than true signal.

As in Rayburn [1986], I observe a monotonic decline in the annual ERC estimate during the sample period. I argue that this evidence is consistent with a temporally increasing measurement error in the firm-specific unexpected earnings.

To test this argument, I divide the sample period into four equal subperiods and identify firms with increasing variance of unexpected earnings across subperiods. The evidence indicates that almost 85% of the sample firms have had at least one variance increase during the sample period. Based on the number of variance increases, I assign firms into one of four groups such that firms with no (three) variance increases are assigned to Group 1 (Group 4). While there is no strong trend in the firm-specific ERC estimates of Group 1, there is a strong temporal decline in those of the other groups. I obtain the opposite result when the firms are grouped by the number of variance decreases. Overall, these results are consistent with temporally increasing measurement error in unexpected earnings.

Since one cannot eliminate measurement error, I provide evidence on the relative levels of inconsistency of the ERC estimates across different levels of measurement error. I use the subperiod variance as a proxy for the absolute level of measurement error, and assign each firm-year to one of four groups based on their relative rank on the subperiod variance. The results indicate that the subperiod variance is a major determinant of the cross-sectional ERC estimates. While the ERC estimates of the low variance group is almost six, that of the high variance level group is less than one. In addition, the annual ERC estimates of the full sample closely follows those of the high variance level group (one fourth of the sample) indicating the dominant effect of this group.

I also derive an expectations model for the change in the variance of unexpected earnings as a function of the changes in the variance of abnormal returns and the coefficient of determination between the two. Based on this model, I show that only a small portion of the change in the variance of unexpected earnings from one variance level group to the next can be explained by the expectations model.

Additional analysis is conducted to control for the effects of the lead-lag differences in the price-earnings relation (see e.g., Kothari and Sloan [1991]). While I find stronger lead (lag) effects for the low (high) variance level groups, none of the inferences are affected by the lead-lag differences.

In summary, the evidence in this essay suggests that measurement error is a major determinant of both the magnitude and the temporal stability of the cross-sectional earnings response coefficient. This implies researchers should exercise caution in both interpreting and in estimating the price-earnings relation.

The rest of the thesis is organized as follows. In Chapter two, I examine the existence of a unit root in earnings as a determinant of the price-earnings relation. In Chapter three, I investigate how measurement error in unexpected earnings contributes to the bias and inter-temporal instability in the earnings response coefficients. Concluding remarks are provided in Chapter four.

Chapter Two

NONSTATIONARITY IN EARNINGS AND EARNINGS RESPONSE COEFFICIENT

In this chapter I examine the impact of the existence/nonexistence of a unit root in earnings on the magnitude of earnings persistence, and on the association between earnings persistence and the earnings response coefficient.

2.1 EARNINGS INNOVATIONS, EARNINGS PERSISTENCE AND STOCK RETURNS

2.1.1 A Price-Earnings Model

The relation between changes in a firm's equity value (ΔEQ_t) and its earnings (I_t) is modelled by the following system (Kormendi and Lipe [1987, p. 325]):

$$\Delta EQ_t = \alpha_0 + \alpha_1 \cdot \epsilon_t + UEQ_t \tag{2.1}$$

where the unexpected earnings, ϵ_t, depends on the existence or otherwise of nonstationarity in earnings. In particular,

$$\epsilon_t = \Delta I_t - (\rho_0 + \sum_{i=1}^{p} \rho_i \cdot \Delta I_{t-i}) \tag{2.2}$$

for earnings series with a unit root (i.e., difference stationary), or for a stationary earnings process (i.e., level stationary).

$$\epsilon_t = I_t - (\rho_0 + \sum_{i=1}^{p} \rho_i \cdot I_{t-i}) \tag{2.3}$$

The term ΔEQ_t is defined as $(P_t + D_t - P_{t-1})$ where P_t is the market value of equity at time t, and D_t is the dollar value of total equity dividends paid during t. The term UEQ_t is that portion of ΔEQ_t unexplained by the earnings innovations. I assume that earnings follow either an autoregressive (AR(p)) process or an integrated autoregressive (IAR(p)) process, with p autoregressive parameters. The terms ρ_0 and ρ_i refer to the intercept and the i-th autoregressive parameter of the time-series models.

2.1.2 Earnings Persistence and Firm Valuation

Consider the following valuation model (Kormendi and Lipe [1987, p. 327]):

$$P_t = \sum_{i=0}^{\infty} \partial^i \cdot (E_t[CF_{t+i}]) \tag{2.4}$$

where CF_t is the cash flow available to equity holders at time t, ∂ equals [1/(1 + r)], and r is the constant rate of interest for discounting expected future cash flows. The term $E_t[\cdot]$ represents expectations conditional on information available at time t. The change in P_t conditional on earnings innovation at time t is denoted by $\Delta EQ_t | \epsilon_t$:

$$\Delta EQ_t | \epsilon_t = \sum_{i=0}^{\infty} \partial^i \cdot \Delta E_t(CF_{t+i} | \epsilon_t) \tag{2.5}$$

If I assume that the present value of revisions in expected future cash flows equals the present value of revisions in expected future earnings, then I can express (2.5) as:[1]

$$\Delta EQ_t | \epsilon_t = \sum_{i=0}^{\infty} \partial^i \cdot \Delta E_t(I_{t+i} | \epsilon_t) \tag{2.6}$$

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[1]This assumption is also made by Kormendi and Lipe [1987, p. 328] and is less restrictive than the standard earnings capitalization assumption that the present value of expected earnings is equal to the present value of expected cash flows. Accounting earnings incorporate accruals and exclude investment outlays and receipts from sale of long-term assets. Consequently, only under special conditions will future earnings equal future cash flows. For example, if depreciation is approximately equal to yearly investment outlays, then earnings would approximate cash flows. In such case, the earnings capitalization assumption may be a reasonable one (Watts and Zimmerman [1986, p. 28]).

This can be rewritten as:

$$\Delta EQ_t | \epsilon_t = [\sum_{i=0}^{\infty} \partial^i \cdot dI_{t+i}/d\epsilon_t] \cdot \epsilon_t \tag{2.7}$$

$$= \Phi(I) \cdot \epsilon_t \tag{2.8}$$

The $\Phi(I)$ is the present value of revisions in current and expected future earnings given one dollar of current earnings innovation (or "unexpected earnings"), which is referred to as the "persistence" of earnings (see Miller and Rock [1985]).

The important point is that the magnitude of $\Phi(I)$ depends on the nature of nonstationarity (or stationarity) in earnings. Assuming earnings follow a nonstationary IAR(p) process, I can rewrite $\Phi(I)$ in terms of the autoregressive parameters (Kormendi and Lipe [1987, p. 330]):

$$\Phi(I) = \frac{1}{(1 - \partial)(1 - \sum_{i=1}^{p} \partial^i \cdot \rho_i)} \tag{2.9}$$

If earnings do not have a unit root, i.e., earnings follow an AR(p) process, then persistence is defined as (Flavin [1981, p. 988]):

$$\Phi(I) = \frac{1}{(1 - \sum_{i=1}^{p} \partial^i \cdot \rho_i)} \tag{2.10}$$

From equation (2.1), we have that

$$\Delta EQ_t | \epsilon_t = \alpha_0 + \alpha_1 \cdot \epsilon_t \tag{2.11}$$

If I assume that α_0 is uncorrelated with earnings innovations, then α_1 (i.e., the earnings response coefficient in (2.11)) should be equal to $\Phi(I)$ (i.e., the earnings persistence in (2.8); see Kormendi and Lipe [1987, p. 330]).

The magnitude of earnings persistence in (2.8) is determined by the nature of time-series properties of earnings. For example, consider the following two earnings series:

$$\text{AR(1):} \qquad I_t = 0.95 \cdot I_{t-1} + u_t \tag{2.12}$$

$$\text{RW:} \qquad I_t = I_{t-1} + u_t \tag{2.13}$$

The AR(1) is a stationary series whereas random walk (RW) is a special case of a nonstationary series with a unit root. If I assume that stock price equals the present value of discounted future earnings with a constant discount rate (e.g., 10%), then the expectation for the earnings response coefficient would be 7.33 for the AR(1) model compared with 11.00 for the RW model (see Kormendi and Lipe [1987, p. 330]). Thus, given a five percent difference (0.95 versus 1.00) in the autoregressive coefficient, the expectation for the earnings response coefficient is off by 50% ((11 - 7.33)/7.33).

To fully appreciate the magnitude of difference in earnings persistence as represented in expressions (2.9) and (2.10), consider the following univariate time-series earnings process:

$$\text{AR(1):} \qquad I_t = \rho_1 \cdot I_{t-1} + u_t \tag{2.14}$$

Several simulated AR(1) series are generated corresponding to various ρ_1 values (specifically ranging from 0.10 to 0.99). First, I assume that one knows the series is stationary and therefore estimates an AR coefficient, ρ^s_1. Second, I assume that one incorrectly differences the series, and estimates an IAR coefficient, ρ^i_1. Corresponding to these two scenarios, I obtain estimates of ρ^s_1 and ρ^i_1. Based on these estimates, I compute the respective earnings persistence using an interest rate of ten percent. Table 2.1 provides various estimates conditional on known ρ_1 values.

Table 2.1
ESTIMATES OF EARNINGS PERSISTENCE FOR A SIMULATED AR(1) PROCESS[1]

ρ_1	ρ^s_1	ρ^i_1	$\Phi^s(I)$	$\Phi^i(I)$	$\Phi^i(I)/\Phi^s(I)$
0.99	0.980	-0.059	9.17	10.44	1.14
0.90	0.883	-0.104	5.07	10.05	1.98
0.80	0.756	-0.140	3.20	9.76	3.05
0.70	0.644	-0.183	2.41	9.43	3.91
0.60	0.536	-0.227	1.95	9.12	4.68
0.50	0.434	-0.271	1.65	8.83	5.35
0.40	0.328	-0.313	1.42	8.56	6.03
0.30	0.228	-0.355	1.26	8.32	6.60
0.20	0.131	-0.397	1.14	8.08	7.09
0.10	0.037	-0.437	1.03	7.87	7.64

[1]The simulations are based on 100 time-series observations. ρ_1 is the true AR(1) coefficient of the level series. ρ^s_1 and ρ^i_1 are estimates of the slope coefficients of the one-period lagged values of the level and differenced series respectively. $\Phi^s(I)$ and $\Phi^i(I)$ are estimates of earnings persistence from the AR(1) and IAR(1) models respectively. Note that ρ_1 equals one represents a nonstationary series with a unit root (i.e., a random walk process).

It is evident from Table 2.1 that as ρ_1 deviates more from one, the difference between an unbiased estimate of $\Phi(I)$ ($\Phi^s(I)$) and an estimate assuming a unit root ($\Phi^i(I)$) increases. Therefore, if earnings series do not have a unit root, then differencing them prior to fitting a time-series model would yield estimates of earnings persistence which significantly deviate from the true earnings persistence.[2] The evidence

[2]The primary objective of studying the earnings response coefficient is to understand how changes in stock prices relate to changes in earnings. The impact of a dollar of unexpected earnings on future values of earnings (and on stock price) depends on the existence of a nonstationary component in earnings. This relation between stock prices

in Table 2.1 suggests that a significant upward bias in the estimate of earnings persistence relative to the earnings response coefficient estimate is indicative of overdifferencing in estimating a time-series model for the earnings series. For instance, conditional on the unit root assumption for earnings, Kormendi and Lipe [1987, Table 1] found a median earnings response coefficient of 2.50 when the median earnings persistence was 8.91. In any event, identifying the existence or otherwise of nonstationarity in earnings should lead to an estimate of earnings persistence that is more comparable to the earnings response coefficient estimate.[3]

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and earnings has an interesting parallel in macroeconomic theory. One well-known paradox in macroeconomics concerns the variability of consumption relative to personal income. The expected variability of consumption depends on the assumption regarding the nature of time series properties of personal income. For example, when personal income is represented as a stationary process, consumption looks too volatile (Flavin [1981]). When personal income is represented as a difference stationary process, consumption looks too smooth (Campbell and Deaton [1987]). Similarly, if an IAR (AR) model is assumed for earnings of all firms, then the stock price changes might look too smooth (too volatile).

[3]Note that inappropriate differencing by itself is not fatal in estimating earnings persistence. The main source of empirical bias is the simple time-series process that is assumed across the board (e.g., IAR(2) by Kormendi and Lipe). To illustrate, consider the following AR(1) process:

$$\text{AR(1)}: \qquad I_t = 0.70 \cdot I_{t-1} + u_t$$

I simulate the above AR(1) series with 1,000 observations. First, the maximum likelihood estimate of the AR(1) coefficient is 0.6866. Assuming a discount rate of 10%, this implies an earnings persistence of 2.66. Secondly, I estimate the following IAR(2) model for this series:

$$\text{IAR(2)}: \qquad \Delta I_t = -0.171 \cdot \Delta I_{t-1} - 0.124 \cdot \Delta I_{t-2} + u_t$$

The estimate of earnings persistence from this model is 8.75. Thus, similar to the results in Table 2.1, the IAR(2) model leads to a significant upward bias in the estimate of earnings persistence. Finally, I estimate a time-series model that best describes the differenced series based on the correlation structure of ΔI_t. The resulting integrated moving average (IMA) model is:

2.2 A TEST FOR A UNIT ROOT IN EARNINGS

2.2.1 Prior Research on Tests of a Unit Root

In order to provide evidence on the effects of nonstationarity on the association between earnings persistence and the earnings response coefficient, I test for existence of a unit root in earnings. The early research in the unit root literature restricted itself to cases where innovations are assumed temporally independent and possess identical variance (see e.g., Fuller [1976], Dickey [1976]). Fuller [1976] and Dickey and Fuller [1979, 1981] extended these tests to the case of IAR models. The tests involved conducting regression equations with lags of first differences of the variable included as additional regressors. Said and Dickey [1984] extended these latter studies to the general class of ARIMA models. Their approach deals with the problem of correlation in first differences of a variable by an autoregressive correction which adds extra lags of first differences as regressors. The number of such extra

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IMA(8): $$\Delta I_t = u_t - 0.319 \cdot u_{t-1} - 0.222 \cdot u_{t-2} - 0.186 \cdot u_{t-3} - 0.066 \cdot u_{t-4} - 0.068 \cdot u_{t-5} - 0.090 \cdot u_{t-6} - 0.050 \cdot u_{t-8}$$

The formula for computing the persistence of an IMA(q) series is given below (see Flavin [1981]):

$$\Phi(I) = (1 + \sum_{i=1}^{q} \partial^{i} \cdot \theta_i)/(1 - \partial)$$

where θ_i is the i-th MA parameter. Assuming a discount rate of 10%, the persistence of the IMA(8) model is 2.49. Compared with the AR(1) model, there is only a 6.4% ((2.49 - 2.66)/2.66) bias in the estimate of earnings persistence from the IMA(8) model as opposed to a 228.9% ((8.75 - 2.66)/2.66) bias in the estimate from the IAR(2) model. Thus, the effect of inappropriate differencing could be offset by fitting more complicated time-series models. However, given the cost of identifying complicated time-series models using Box-Jenkins methodology, it may be more efficient to test for the existence of a unit root before estimating time-series models.

lags is an increasing function of the sample size (n) not exceeding $n^{1/3}$. Additional "nuisance parameters" need to be estimated which, in effect, reduce the effective number of observations.

A recent test proposed by Phillips [1987] uses a nonparametric correction to deal with the correlation in first differences. This method does not require estimation of additional nuisance parameters and thereby avoids reduction in the effective number of observations. This method is valid in a more general context since weaker conditions are imposed on the innovations of the series. In fact, a wide variety of possible data generating mechanisms are permitted. For example, any ARMA model with a unit root and ARMAX systems with a unit root and stable exogenous processes that admit a Wold decompositon is permitted. Phillips and Perron [1986] and Perron [1986b] further extend this approach to allow for the presence of a non-zero mean and a non-zero drift.

The main advantage of this new method is its ease of implementation. The tests involve estimating a first-order AR model by OLS and correcting/transforming the test statistics by a factor based on the structure of the residuals from this regression. The asymptotic critical values of these transformed statistics are the same as those tabulated by Dickey and Fuller. Thus, the Phillips-Perron method involves a relatively easy test for a unit root with possibly heterogeneously and dependently distributed data. Statistical efficiency is not compromised by using these transformed statistics when there is no need for them, i.e., when errors are i.i.d. (independently and identically distributed). This is because the Phillips-Perron tests have the same asymptotic local power under general error structures as the Dickey-Fuller original statistics have under i.i.d. errors.

2.2.2 Description of Phillips-Perron Tests

Consider two possible data generating mechanisms:

$$I_t = I_{t-1} + u_t \tag{2.15}$$

$$I_t = \mu + I_{t-1} + u_t \tag{2.16}$$

where I_t is an earnings series, μ is the drift parameter, and u_t is the innovation of the series. To complete the specification of the model, a set of relatively unrestrictive assumptions is imposed on the innovations, i.e., u_t (see Perron [1986c, p. 6] for a list of assumptions). These assumptions permit many dependent and heterogeneously distributed time series (e.g., ARMA with a unit root).

Consider the following OLS regression involving I_t for a sample size of (n+1) where I_t is generated by either model (2.15) or (2.16):

$$I_t = \mu + b \cdot (t - n/2) + a \cdot I_{t-1} + u_t \tag{2.17}$$

The unit root test involves conducting a statistical test of the null hypothesis that a is equal to one. Phillips [1987], Phillips and Perron [1986] and Perron [1986b] derive several test statistics to identify the nature of nonstationarity in a time series process. Perron [1986c] provides a list of these test statistics along with the null hypothesis tested and the sources of critical values. In this study, $Z(t_a)$ is chosen as the unit root test statistic.[4] For each firm, regression model (2.17) is estimated and the standard t-statistic, denoted t_a, is constructed to test the null hypothesis that a is equal to one. $Z(t_a)$ is

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[4]Perron [1986c, pp. 20–21] proposes a more cautious approach in which more than one test statistic (see Table 1 of Perron for a list of these statistics.) would be used in a sequential manner to test for a unit root. Based on a pilot study, I found that the sequential approach did not materially alter any of the inferences compared with using only the $Z(t_a)$ statistic. This could be due to the limited number of time-series observations available in my study (see also n. 5). Therefore, I decided to simplify the analysis by employing only the $Z(t_a)$ statistic.

obtained by transforming t_a by a factor based on the structure of the residuals from the regression model (2.17). The procedure used in computing $Z(t_a)$ is described in Appendix A. The critical values for $Z(t_a)$ are tabulated in Fuller [1976, p. 373]. In order to test for the effect of a unit root on earnings persistence, firms are sorted by the value of $Z(t_a)$ in descending order. Using the quartile values of $Z(t_a)$, firms are assigned into four groups with firms in Group 1 (Group 4) having the highest (lowest) probability of a unit root.[5]

2.3 DERIVATION OF THE HYPOTHESES

Since specification errors could muddle the one-to-one correspondence between α_1 and $\Phi(I)$, I test the less restrictive hypothesis that α_1 is (positively) linearly related to $\Phi(I)$.[6] To conduct a test of this hypothesis, I compute earnings persistence and earnings response coefficients using a two step procedure. To replicate Kormendi and Lipe's study, I fit a differenced stationary univariate time-series model (equation (2.2)) to each firm's earnings; based on this model, earnings innovations ($\epsilon^i{}_t$) and earnings persistence ($\Phi^i(I)$ (equation (2.9)), are

[5]An alternative approach would have been to assign firms into two groups - "Unit Root" and "No Unit Root" - based on a chosen alpha level when conducting the unit root test using the $Z(t_a)$ statistic. Given the limited number of time series observations available in this study (median number of observations = 38) and the asymptotic nature of the unit root tests, such an approach would have resulted in very few firms being grouped under the "No Unit Root" category, thus severely limiting the power of this approach.

[6]Kormendi and Lipe [1987, p. 331] provide additional arguments for why a test based on the equality of α_1 and $\Phi(I)$ would be overly restrictive.

computed.[7] In the second-step, ΔEQ_t is regressed on ϵ^i_t (separately for each firm) to estimate firm-specific earnings response coefficients, α^i_1.[8,9] To test whether the nature of nonstationarity in earnings significantly affects the association between α_1 and $\Phi(I)$, I first estimate a stationary univariate time-series model (equation (2.3)) for each firm. Based on this model, earnings innovations (ϵ^s_t) and earnings persistence ($\Phi^s(I)$ (equation (2.10)) are computed; after which α^s_1 is estimated by regressing ΔEQ_t on ϵ^s_t for each firm.

I conduct two types of tests for positive association between α_1 and $\Phi(I)$. First, the following hypotheses are tested using the Pearson product moment correlation (r(P)) and Spearman rank correlation (r(S)):[10]

H_1: $r^i(i) > 0$, i = P or S

H_2: $r^s(i) > 0$, i = P or S

H_3: $r^s(i) >$ or $< r^i(i)$, i = P or S

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[7]Undeflated earnings are used in fitting time-series models and estimating earnings persistence and the earnings response coefficient. This is because the present study investigates how time-series properties of earnings itself rather than a measure of accounting rate of return (e.g., earnings divided by price, earnings divided by net worth, etc.) relates to stock price movements.

[8]An alternative approach would be to jointly estimate equations (2.1) and (2.2) or equations (2.1) and (2.3) and obtain $\Phi(I)$ and α_1 simultaneously. Kormendi and Lipe [1987, n. 8] found that the two-step procedure yielded results similar to those from joint estimation.

[9]In the empirical version of model (2.1), ΔEQ_t is computed as follows:

$$\Delta EQ_t = P_{t'} + D_{t'} - P_{(t-1)'}$$
$$= \Delta P_{t'} + D_{t'}$$

where $P_{t'}$ is the market value of equity three months after the fiscal year-end t, and $D_{t'}$ is the dollar value of total dividend paid from (t-1)' to t'. For example, for a firm with year-end of December 31, 1986, ΔEQ_t would be computed by adding the change in market value of equity from April 1, 1986 to March 31, 1987 to the dollar value of dividends paid during that period.

[10]All hypotheses are stated in the alternative form.

where $r^i(i)$ ($r^s(i)$) is a correlation coefficient between α^i_1 (α^s_1) and $\Phi^i(I)$ ($\Phi^s(I)$). Hypothesis H_3 provides indirect evidence on whether earnings, in general, are better described by an IAR(p) or an AR(p) process. The greater the correlation between α^i_1 (α^s_1)and $\Phi^i(I)$ ($\Phi^s(I)$), the greater the likelihood that earnings are better described by a nonstationary (stationary) process.

The second test involves estimating the following OLS regression:

$$\alpha_{1i} = \gamma_0 + \gamma_1 \cdot \Phi_i(I) + \nu_i \qquad (2.18)$$

where $\alpha_{1i} = \alpha^i_{1i}$ or α^s_{1i}, and $\Phi_i(I) = \Phi^i_i(I)$ or $\Phi^s_i(I)$. Superscript i (s) are used for γ_0 and γ_1 to denote estimates when α^i_{1i} (α^s_{1i}) and $\Phi^i_i(I)$ ($\Phi^s_i(I)$) are used in the regression model. Based on these regressions, the following hypotheses are tested:

H_4: $\gamma^i_1 > 0$

H_5: $\gamma^s_1 > 0$

H_6: $\gamma^s_1 <$ or $> \gamma^i_1$

The logic behind hypotheses H_4 through H_6 is similar to that of H_1 through H_3.

The analysis is replicated for each of the four groups separately to isolate the effects of nonstationarity in earnings on the association between earnings response coefficients and earnings persistence. Based on the group-wise analysis, the following hypotheses are tested:

H_7: $r^i_1(i) > r^i_2(i) > r^i_3(i) > r^i_4(i)$, $i = P$ or S

H_8: $r^s_1(i) < r^s_2(i) < r^s_3(i) < r^s_4(i)$, $i = P$ or S

H_9: $r^i_j(i) <$ or $> r^s_j(i)$, $i = P$ or S, $j=1,\ldots,4$

where $r^i_j(i)$ ($r^s_j(i)$) is the correlation coefficient between earnings persistence and the earnings response coefficient for the j-th group assuming an IAR (AR) process in earnings.

Hypothesis H_7 predicts that the correlation between earnings persistence and the earnings response coefficient, assuming a unit root in earnings, would be higher (lower) for the group with the higher (lower) probability of a unit root in earnings. Similarly, hypothesis H_8 predicts that the correlation between earnings persistence and the earnings response coefficient from the AR model, assuming a stationary series, would be higher (lower) for the group with the lower (higher) probability of a unit root in earnings. This is conditional on the prediction that the IAR model is most misspecified for Group 4 whereas the AR model is most misspecified for Group 1. For hypothesis H_9, it is difficult a priori to predict the expected direction for all four groups. Conditional on H_7 and H_8, Hypothesis H_9 predicts $r^i{}_1(i)$ to be greater than $r^s{}_1(i)$ and $r^i{}_4(i)$ to be less than $r^s{}_4(i)$. For groups 2 and 3, the predictions of H_9 depend on whether the AR or IAR model is more descriptive for a particular group.

2.4 EMPIRICAL RESULTS

2.4.1 Sample Selection Procedure

Firms included in this study must meet the following criteria: (1) Stock price and dividend data available for at least 300 months in the 1987 version of the NYSE monthly CRSP tape, and (2) continuous data on "income before extraordinary items and discontinued operations" (IBED) available for at least 15 years in the 1987 version of the Annual and/or Research Compustat tape. The above criteria yield a sample of 449 firms with at least (at most) 19 (39) time-series observations for IBED. The median number of observations is 38.[11]

2.4.2 Time-Series Properties of Annual Earnings

In fitting the AR and IAR models, a maximum lag length of five years is considered (i.e., p=5). Only those coefficients that are significant at the 0.25 level are included in the model.[12] Table 2.2 provides descriptive information on the coefficient estimates of the time series models.[13] Panels A and B provide results for AR(5) and IAR(5) models respectively.

Panel A of Table 2.2 indicates that, based on cross-sectional t-statistics, ρ^*_1 and ρ^*_3 are significantly greater than zero whereas ρ^*_4 is significantly less than zero for the overall sample. The ρ^*_1 value is individually significant for nearly 90% of firms whereas ρ^*_2 through ρ^*_5 are significant for less than 30% of firms. The mean (median) ρ^*_1 is 0.651

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[11]This definition for earnings is consistent with that of Kormendi and Lipe [1987, p. 326]. Furthermore, inclusion of extraordinary items, which are primarily transitory in nature, would likely induce measurement error in the estimates of the time series coefficients.

[12]Kormendi and Lipe [1987] assumed an IAR(2) model for all firms in their sample. In this respect, this study extends Kormendi and Lipe since an attempt is made to fit "firm-specific" time series models. Given the limited number of time series observations available, a liberal alpha level is chosen in identifying significant autoregressive coefficients. Note that a large lag length of five is chosen in order to capture any moving average parameters. Consistent with the time series models, a lag length of five (i.e., ℓ=5) is also chosen in constructing the unit root test statistic.

[13]The STEPAR method of the FORECAST procedure in SAS is used to estimate both the AR and IAR models. First, autocovariances are computed for the number of lags specified, e.g., 5 in the present study. Second, current values are regressed against lagged values using the autocovariances from the previous step in a Yule-Walker framework. Third, the autoregressive parameter that is least significant is identified. If the significance level is greater than the prespecified alpha level (0.25 in the present study), then the parameter is removed from the model. This process is continued until only significant autoregressive parameters remain.

Table 2.2
DESCRIPTIVE INFORMATION ON TIME-SERIES COEFFICIENTS FOR IBED[1]

Panel A: AR(5) Model

Variable	Mean	Median	Minimum	Maximum	Std. Dev.	t-Stat	% Sig
NOBS	35.639	38.000	19.000	39.000			
ρ^{s}_1	0.651	0.725	−0.204	1.327	0.331	41.629c	89.90
ρ^{s}_2	0.007	0.000	−1.056	0.818	0.213	0.663	28.29
ρ^{s}_3	0.037	0.000	−0.656	0.753	0.186	4.235c	27.84
ρ^{s}_4	−0.030	0.000	−0.490	0.548	0.132	−4.796c	20.71
ρ^{s}_5	0.001	0.000	−0.461	0.419	0.097	0.288	14.25

Panel B: IAR(5) Model

Variable	Mean	Median	Minimum	Maximum	Std. Dev.	t-Stat	% Sig
NOBS	34.639	37.000	18.000	38.000			
ρ^{i}_1	−0.089	0.000	−0.953	0.817	0.354	−5.355c	58.13
ρ^{i}_2	−0.122	0.000	−0.968	0.778	0.268	−9.641c	51.22
ρ^{i}_3	−0.024	0.000	−0.798	0.625	0.209	−2.392c	34.74
ρ^{i}_4	−0.047	0.000	−0.718	0.458	0.177	−5.616c	27.17
ρ^{i}_5	−0.007	0.000	−0.524	0.483	0.130	−1.157	21.38

[1]The descriptive information is based on a sample of 449 firms. A 'c' (b/a) indicates statistical significance at the 0.01 (0.05/0.10) level, one-tailed tests. NOBS refers to the number of observations used in estimating the time-series models. ρ^{s}_1 through ρ^{s}_5 are the estimates of autoregressive parameters for IBED in levels (see equation (2.3)). ρ^{i}_1 through ρ^{i}_5 are the estimates of autoregressive parameters for differenced IBED (see equation (2.2)). '% Sig' refers to the percentage of firms for which the autoregressive parameter is significant at the 0.25 level.

(0.725) which suggest that differencing the earnings series for all firms is inappropriate in estimating time series models.

It is evident from panel B of Table 2.2 that, based on cross-sectional t-statistics, ρ^i_1 through ρ^i_4 are significantly less than zero. In addition, ρ^i_1 and ρ^i_2 are individually significant for more than 50% of the firms. The negative mean values of ρ^i_1 through ρ^i_5 suggest that assuming an IAR model for all firms will, on average, lead to overdifferencing of the earnings series. Furthermore, if earnings series are differenced, fitting an IAR(2) model (as in Kormendi and Lipe [1987]) is unlikely to capture the correlation structure of earnings series.

2.4.3 <u>Descriptive Information on Earnings Persistence and Earnings Response Coefficients</u>

Panels A and B of Table 2.3 provide descriptive information on earnings response coefficients and earnings persistence from IAR and AR models respectively. A discount rate of ten percent is assumed for estimating the earnings persistence.[14] The results in panel A represent a replication of Kormendi and Lipe's study on a larger sample.[15]

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[14]Kormendi and Lipe [1987, Table 3] found that the correlation between earnings persistence and earnings response coefficients was not materially affected by the choice of discount rate in the range of 5% to 30%. This finding is supported by the replication (results not reported) of the correlation analysis reported in Tables 2.4 through 2.8 assuming discount rates of 5% and 20%.

[15]Note that Kormendi and Lipe [1987] removed market-wide effects and inflation effects from both the stock returns and earnings series. This procedure is not adopted in the present study for the following reasons:

(i) The time-series properties of market-adjusted earnings could be affected by the equilibrium relation between firm earnings and market-wide earnings. For example, if firm earnings and market earnings are cointegrated (i.e., have a common stochastic trend), then the market-adjusted earnings would be a stationary series with no unit root. Thus, the removal of market-wide effects may be unwarranted in the present context unless one can hypothesize on the effects of market-wide earnings on firm-specific earnings persistence.

Table 2.3
DESCRIPTIVE INFORMATION ON EARNINGS PERSISTENCE AND EARNINGS RESPONSE COEFFICIENTS[1]

Panel A: IAR(5) Model[2]

Variable	Mean	Minimum	First Quartile	Median	Third Quartile	Maximum	% Sig
N	32.241	16.000	28.000	35.000	36.000	37.000	
α^{i}_{1}	3.293	-7.990	-0.017	1.180	3.910	62.760	34.97
$t(\alpha^{i}_{1})$	1.146	-6.889	-0.016	1.073	2.113	9.635	
p-value	0.288	0.000	0.022	0.147	0.506	0.999	
R^2	0.104	0.000	0.011	0.056	0.141	0.732	
$\Phi^{i}(I)$	11.360	2.924	6.860	9.173	13.461	50.288	

Panel B: AR(5) Model[3]

Variable	Mean	Minimum	First Quartile	Median	Third Quartile	Maximum	% Sig
N	32.980	17.000	28.000	36.000	37.000	38.000	
α^{s}_{1}	2.920	-4.061	0.387	1.782	4.430	22.058	49.44
$t(\alpha^{s}_{1})$	1.843	-3.845	0.372	1.665	3.030	9.950	
p-value	0.209	0.000	0.002	0.053	0.356	0.999	
R^2	0.149	0.000	0.020	0.086	0.237	0.739	
$\Phi^{s}(I)$	3.459	0.688	2.000	3.448	4.830	7.213	

[1]The descriptive information is based on a sample of 449 firms. 'p-value' refers to the probability of observing a value less than $t(\alpha_1)$ from the t-distribution. '% Sig' refers to the percentage of firms for which the price-earnings relation is significant at the 0.05 level (one-tailed). 'N' refers to the number of observations used in estimating the price-earnings relation.

(ii) Secondly, the analysis of market-adjusted earnings would fail to provide insights into the time-series properties of accounting earnings.

(iii) Thirdly, the primary findings of Kormendi and Lipe have been replicated using undeflated stock price and earnings data. Both the results of correlation analysis and the magnitude of earnings persistence reported are similar to those of Kormendi and Lipe (see Table 2.4).

Table 2.3 (Cont'd.).

[2]$\Phi^i(I)$ is the estimate of earnings persistence from the IAR(5) model for IBED, assuming a discount rate of 10% (see equation (2.9)). α^i_1, $t(\alpha^i_1)$, and R^2 are the slope coefficient (or the earnings response coefficient), t-statistic of the slope coefficient, and the coefficient of determination from the regression of change in equity value on earnings innovation from the IAR process (see equation (2.11)).

[3]$\Phi^s(I)$ is the estimate of earnings persistence from the AR(5) model for IBED, assuming a discount rate of 10% (see equation (2.10)). α^s_1, $t(\alpha^s_1)$, and R^2 are the slope coefficient (or the earnings response coefficient), t-statistic of the slope coefficient, and the coefficient of determination from the regression of change in equity value on earnings innovation from the AR process (see equation (2.11)).

The mean (median) earnings response coefficient (α^i_1) in the present study is 3.293 (1.180) for a sample of 449 firms compared with 3.380 (2.500) in Kormendi and Lipe's study for a sample of 145 firms. The mean (median) persistence ($\Phi^i(I)$) in the present study is 11.360 (9.173) compared with 9.930 (8.910) in Kormendi and Lipe's study. The results in panel A indicate that the mean (median) α^i_1 is more than three (seven) times smaller than the mean (median) $\Phi^i(I)$. Although the difference between earnings persistence and earnings response coefficients is more pronounced in this study, the evidence is consistent with that of Kormendi and Lipe.

For the AR model from panel B, the mean (median) earnings response coefficient (α^s_1) is 2.920 (1.782) compared with the mean (median) earnings persistence of 3.459 (3.448). While the mean $\Phi^s(I)$ is 18% greater than the mean α^s_1, the median $\Phi^s(I)$ is nearly twice the median α^s_1. A comparison between panels A and B shows that the upward bias in earnings persistence (compared with the earnings response coefficient) is more pronounced in panel A, suggesting that, on average, earnings are better described by an AR process in estimating earnings persistence. This inference is consistent with the time-series properties of earnings reported in Table 2.2.

The price-earnings relation is statistically significant for a larger number of firms for the AR model (49.44%) compared with that of the IAR model (34.97%). The median p-value is 0.053 in panel B compared with 0.147 in panel A, and the median R^2 for the price-earnings regression is 8.6% for the AR model compared with 5.6% for the IAR model. Thus, on average, earnings are better described by an AR process for estimating the earnings persistence <u>and</u> for estimating the price-earnings relation.

2.4.4 Tests of Association Between Earnings Persistence and Earnings Response Coefficients

Panel A of Table 2.4 provides results of correlation tests between earnings persistence and the earnings response coefficient whereas panel B presents the regression results. The Pearson and Spearman correlations are positive and statistically significant at the 0.01 level for both the AR and IAR models. For the IAR model, correlations of 0.542 and 0.350 are obtained for my sample compared with 0.390 and 0.310 obtained by Kormendi and Lipe. The regression results reported in panel B for the IAR model reinforce the correlation results. The slope coefficient of 0.602 is nearly twice the magnitude of 0.350 obtained by Kormendi and Lipe. Although the results in Table 2.4 support hypotheses H_1 and H_4, they do not support the more stringent hypothesis of $\gamma^i{}_1$ equal to one (the t-statistic for γ_1=1 is -9.01, see panel B).

The correlation results for the AR(5) model are qualitatively similar to those of the IAR(5) model. However, the slope coefficient of 0.892 for $\Phi^s(I)$ is <u>not</u> significantly different from one, the theoretical expectation for γ_1. Thus, these results not only support H_2 and H_5, but also provide evidence consistent with the more stringent hypothesis that $\gamma^s{}_1$ is equal to one. However, the correlation results provided in Table 2.4 do not provide any strong evidence for choosing one time-series model over the other.

Table 2.5 provides correlations among the two sets of earnings persistence and earnings response coefficients. The Pearson (Spearman) correlation between the two measures of earnings response coefficient is 0.795 (0.841), whereas the Pearson (Spearman) correlation between the two sets of earnings persistence is only 0.480 (0.590).

Table 2.4
ASSOCIATION BETWEEN EARNINGS PERSISTENCE AND EARNINGS RESPONSE COEFFICIENT[1]

Panel A: Correlation of Earnings Persistence and Earnings Response Coefficient[2]

Model	r(P)	r(S)
IAR(5)	0.542c	0.350c
AR(5)	0.381c	0.476c

Panel B: Regression of Earnings Response Coefficient on Earnings Persistence[3]

$$\alpha_{1i} = \gamma_0 + \gamma_1 \cdot \Phi_i(I) + \nu_i$$

Model	γ_0	γ_1	$t(\gamma_1=1)$	F-Ratio	R^2
IAR(5)	-3.546c	0.602c	-9.010c	185.704c	0.294
	(-6.055)	(13.627)			
AR(5)	-0.166	0.892c	-1.055	76.091c	0.146
	(-0.422)	(8.723)			

[1]The analysis is based on a sample of 449 firms. A 'c' (b/a) indicates statistical significance at the 0.01 (0.05/0.10) level, one-tailed tests.

[2]r(P) (r(S)) refers to Pearson (Spearman) correlation coefficient between earnings persistence (Φ(I)) and earnings response coefficient (α_1).

[3]The number in parentheses refers to t-statistic.

Table 2.5
CORRELATION BETWEEN THE TWO SETS OF EARNINGS PERSISTENCE AND EARNINGS RESPONSE COEFFICIENTS[1]

	α^{i}_{1}	$\Phi^{s}(I)$	$\Phi^{i}(I)$
α^{s}_{1}	0.795 (0.841)	0.381 (0.476)	0.603 (0.544)
α^{i}_{1}		0.193 (0.243)	0.542 (0.350)
$\Phi^{s}(I)$			0.480 (0.590)

[1]The analysis is based on a sample of 449 firms. The numbers given in the table are Pearson (Spearman) correlations. All correlations reported are significant at the 0.01 level, one-tailed tests. $\Phi^{s}(I)$ and $\Phi^{i}(I)$ are the earnings persistence measures obtained assuming an AR model in level and differenced earnings respectively. α^{s}_{1} and α^{i}_{1} are the earnings response coefficients obtained assuming an AR model in level and differenced earnings respectively.

This suggests that assumptions about the nature of the time-series process of earnings (AR versus IAR) have a greater impact on the measurement of earnings persistence relative to the earnings response coefficient. Thus, the choice of time-series model is more critical in the estimation of earnings persistence compared with the earnings response coefficient.

Table 2.6 provides the results of correlation and regression analysis for four sub-samples of firms grouped by the probability of a unit root in earnings. Recall that firms in Group 1 (Group 4) have the higher (lower) probability of a unit root in earnings. Panels A and B provide the median values of $Z(t_a)$ (i.e., the unit root test statistic), a (the slope of one period lagged earnings variable in regression equation (2.17)), $\Phi(I)$ (earnings persistence), and α_1 (earnings response coefficient) of the four sub-samples for the IAR and AR models respectively. Pearson and Spearman correlations between earnings persistence and earnings response coefficients are also reported.

The existence of a unit root is supported only for Group 1 which has a median equal to 1.014. The correlations reported in panel A indicate that the IAR model performs well only for Group 1. For these firms, the Pearson (Spearman) correlation between earnings persistence and earnings response coefficient is 0.490 (0.436) which is significant at the 0.01 level. However, for firms in Groups 2,3, and 4, the association between earnings persistence and the earnings response coefficient is insignificant. Thus, the significant results from the IAR model (see Table 2.4) are due to firms in Group 1. The Spearman correlations for Groups 1 through 4 are also consistent with hypothesis H_7 suggesting that the IAR model is descriptive of earnings of firms in

Table 2.6
ASSOCIATION BETWEEN EARNINGS PERSISTENCE AND EARNINGS RESPONSE COEFFICIENT OF FIRMS GROUPED BY THE PROBABILITY OF UNIT ROOT IN IBED[1]

Panel A: Correlations for the IAR(5) Model[2]

Group	n	$Z(t_a \mid \ell=5)$	a	$\Phi^i(I)$	α^i_1	r(P)	r(S)
1	111	0.689	1.014	15.708	4.570	0.490c	0.436c
2	113	-1.172	0.809	11.000	1.207	-0.012	0.075
3	113	-2.039	0.603	8.772	0.992	0.013	0.056
4	112	-3.291	0.218	6.142	0.442	0.029	-0.041

Panel B: Correlations for the AR(5) Model[3]

Group	n	$Z(t_a \mid \ell=5)$	a	$\Phi^s(I)$	α^s_1	r(P)	r(S)
1	111	0.689	1.014	4.331	5.361	0.291c	0.349c
2	113	-1.172	0.809	4.554	2.427	0.458c	0.478c
3	113	-2.039	0.603	3.262	1.264	0.290c	0.322c
4	112	-3.291	0.218	1.785	0.647	-0.016	0.106

Panel C: Regression Results for the IAR(5) Model

$$\alpha^i_{1i} = \gamma_0 + \gamma_1 \cdot \Phi^i_i(I) + \nu_i$$

Group	n	γ^i_0	γ^i_1	$t(\gamma^i_1=1)$	F-Ratio	R^2
1	111	-3.368a	0.678c	-2.789c	34.421c	0.240
		(-1.421)	(5.867)			
2	113	2.048b	-0.011	-11.074c	0.015	0.000
		(1.824)	(-0.121)			
3	113	1.477a	0.016	-8.457c	0.018	0.000
		(1.342)	(0.136)			
4	112	0.366	0.037	-8.051c	0.095	0.001
		(0.468)	(0.307)			

Table 2.6 (Cont'd.).

Panel D: Regression Results for the AR(5) Model

$$\alpha^s_{1i} = \gamma_0 + \gamma_1 \cdot \Phi^s_i(I) + \nu_i$$

Group	n	γ^s_0	γ^s_1	$t(\gamma^s_1 - 1)$	F-Ratio	R^2
1	111	1.429	1.253c	0.640	10.062c	0.085
		(0.866)	(3.172)			
2	113	-0.477	0.774c	-1.587a	29.424c	0.210
		(-0.742)	(5.424)			
3	113	0.148	0.440c	-4.073c	10.223c	0.084
		(0.270)	(3.197)			
4	112	0.833c	-0.025	-6.951c	0.030	0.000
		(2.471)	(-0.172)			

[1]A 'c' (b/a) indicates statistical significance at the 0.01 (0.05/0.10) level, one-tailed tests. The number in parentheses refers to t-statistic. Firms are assigned to the four groups based on descending values of $Z(t_a|\ell=5)$, the unit root test statistic. 'n' refers to the number of firms in each group. $\Phi^i(I)$ ($\Phi^s(I)$) is the estimate of earnings persistence from the IAR (AR) model for IBED, assuming a discount rate of 10%. α^i_1 (α^s_1) is the earnings response coefficient obtained assuming an IAR (AR) model for IBED. 'a' refers to the slope of one period lagged earnings variable in regression equation (2.17).

[2]For each group, median values of $Z(t_a|\ell=5)$, a, $\Phi^i(I)$, and α^i_1 are reported. r(P) (r(S)) refers to Pearson (Spearman) correlation coefficient between $\Phi^i(I)$ and α^i_1.

[3]For each group, median values of $Z(t_a|\ell=5)$, a, $\Phi^s(I)$, and α^s_1 are reported. r(P) (r(S)) refers to Pearson (Spearman) correlation coefficient between $\Phi^s(I)$ and α^s_1.

Group 1 only.

The results in panel B show a significant correlation between earnings persistence and the earnings response coefficient (using the AR model) in three of four groups. The correlations for Group 4 are not statistically significant. While the significant correlations found for Groups 2 and 3 are consistent with my hypotheses, those for Group 4 are inconsistent with hypothesis H_8. In the next section, I consider whether measurement error in the earnings response coefficient accounts for the inconsistent evidence for hypothesis H_8.

A comparison of panels A and B provides evidence in support of hypothesis H_9. For Group 1, the Spearman correlation of the IAR model (0.436) is greater than that of the AR model (0.349); whereas for groups 2–4 the Spearman correlation of the AR model is greater than that of the IAR model. This evidence indicates that the unit root assumption is inappropriate for groups 2–4.

The regression results are reported in panels C and D for the IAR and AR models respectively. The intercept (−3.368) and slope coefficient (0.678) reported in Group 1 for the IAR model are very similar to those for the overall sample reported in Table 2.4. For the AR model, while γ^{s}_1 is significant for Groups 1 through 3, the magnitude of γ^{s}_1 is monotonically decreasing. The slope coefficient of 1.253 for Group 1 is insignificantly different from one (see $t(\gamma_1 - 1)$) whereas for Groups 2 and 3, it is significantly different from one at the 0.10 and 0.01 levels respectively. Comparison of slope coefficients across the two models indicates that the slope coefficient for the AR model is larger than that of the IAR model for the first three groups. This suggests that if the IAR model is chosen for all firms there is a greater probability of rejecting excess volatility in stock prices based on the magnitude of the earnings response coefficient. Overall, the results reported in Table 2.6 are consistent with the argument that the existence of a stochastic nonstationary component in earnings is a significant determinant of the earnings response coefficient.

2.4.5 Ex Post Identification of Measurement Error in Earnings Response Coefficients

If measurement error in the earnings response coefficient monotonically increases from Group 1 to Group 4, then it is difficult to isolate the effects predicted by Hypothesis H_8. To control for this possibility, the sign of the earnings response coefficient is chosen as an ex post signal of measurement error. Theoretically, the earnings response coefficient is expected to be positive. Therefore, I view negative values as a sign of measurement error. Empirically, 25.2% of the firms have a negative earnings response coefficient for the IAR model compared with 18.5% for the AR model. The evidence also indicates that the probability of a negative earnings response coefficient is negatively associated with the probability of a unit root in earnings. For the IAR (AR) model, 14.4% (6.3%) of firms in Group 1 have negative values for earnings response coefficients compared with 29.5% (28.6%) for Group 4. To test the impact of measurement error on the association between earnings persistence and the earnings response coefficient, the analyses in Tables 2.4 and 2.6 are replicated for firms with positive earnings response coefficients; the results are reported in Tables 2.7 and 2.8 respectively.

Comparing the results in Table 2.4 versus Table 2.7, it is evident that the association between earnings persistence and the earnings response coefficient improves once firms with negative earnings response

Table 2.7
ASSOCIATION BETWEEN EARNINGS PERSISTENCE AND EARNINGS RESPONSE COEFFICIENT FOR FIRMS WITH POSITIVE EARNINGS RESPONSE COEFFICIENTS[1]

Panel A: Correlation of Earnings Persistence and Earnings Response Coefficient[2]

Model	n	r(P)	r(S)
IAR(5)	336	0.611c	0.557c
AR(5)	366	0.408c	0.573c

Panel B: Regression of Earnings Response Coefficient on Earnings Persistence[3]

$$\alpha_{1i} = \gamma_0 + \gamma_1 \cdot \Phi_i(I) + \nu_i$$

Model	n	γ_0	γ_1	$t(\gamma_1 = 1)$	F-Ratio	R^2
IAR(5)	336	-2.981c	0.676c	-6.755c	199.214c	0.374
		(-4.501)	(14.114)			
AR(5)	366	0.406	0.939c	-0.555	72.652c	0.166
		(0.936)	(8.524)			

[1]A 'c' (b/a) indicates statistical significance at the 0.01 (0.05/0.10) level, one-tailed tests.

[2]r(P) (r(S)) refers to Pearson (Spearman) correlation coefficient between earnings persistence ($\Phi(I)$) and earnings response coefficient (α_1).

[3]The number in parentheses refers to t-statistic.

Table 2.8
ASSOCIATION BETWEEN EARNINGS PERSISTENCE AND EARNINGS RESPONSE COEFFICIENT
FOR FIRMS WITH POSITIVE EARNINGS RESPONSE COEFFICIENTS
GROUPED BY THE PROBABILITY OF UNIT ROOT IN IBED[1]

Panel A: Correlations for the IAR(5) Model[2]

Group	n	$Z(t_a \mid \ell=5)$	a	$\Phi^i(I)$	α^i_1	r(P)	r(S)
1	95	0.697	1.025	16.929	6.313	0.511c	0.456c
2	82	−1.159	0.819	11.000	2.523	0.143a	0.321c
3	80	−2.043	0.604	8.758	1.780	0.166a	0.299c
4	79	−3.292	0.234	6.087	0.981	0.189b	−0.015

Panel B: Correlations for the AR(5) Model[3]

Group	n	$Z(t_a \mid \ell=5)$	a	$\Phi^s(I)$	α^s_1	r(P)	r(S)
1	104	0.676	1.016	4.390	5.839	0.210b	0.265c
2	95	−1.163	0.826	4.683	3.157	0.506c	0.535c
3	87	−2.039	0.603	3.351	2.008	0.437c	0.554c
4	80	−3.245	0.232	1.785	1.005	0.143a	0.266c

Panel C: Regression Results for the IAR(5) Model

$$\alpha^i_{1i} = \gamma_0 + \gamma_1 \cdot \Phi^i_i(I) + \nu_i$$

Group	n	γ^i_0	γ^i_1	$t(\gamma^i_1 = 1)$	F-Ratio	R^2
1	95	−2.414	0.706c	−2.389c	32.872c	0.261
		(−0.931)	(5.773)			
2	82	2.098b	0.121a	−9.404c	1.679	0.021
		(1.885)	(1.296)			
3	80	1.232	0.180a	−6.779c	2.200	0.027
		(1.072)	(1.483)			
4	79	0.118	0.208b	−6.422c	2.861a	0.036
		(0.149)	(1.691)			

Table 2.8 (Cont'd.).

Panel D: Regression Results for the AR(5) Model

$$\alpha^s_{1i} = \gamma_0 + \gamma_1 \cdot \Phi^s_i(I) + \nu_i$$

Group	n	γ^s_0	γ^s_1	$t(\gamma^s_1-1)$	F-Ratio	R^2
1	104	3.163b	0.916c	-0.200	4.726b	0.044
		(1.766)	(2.174)			
2	95	0.323	0.740c	-1.994b	32.078c	0.257
		(0.539)	(5.664)			
3	87	0.215	0.631c	-2.627c	20.116c	0.191
		(0.384)	(4.485)			
4	80	0.991c	0.196a	-5.226c	1.619	0.020
		(2.861)	(1.272)			

[1]A 'c' (b/a) indicates statistical significance at the 0.01 (0.05/0.10) level, one-tailed tests. The number in parentheses refers to t-statistic. Firms are assigned to the four groups based on descending values of $Z(t_a|\ell=5)$, the unit root test statistic. 'n' refers to the number of firms in each group. $\Phi^i(I)$ ($\Phi^s(I)$) is the estimate of earnings persistence from the IAR (AR) model for IBED, assuming a discount rate of 10%. α^i_1 (α^s_1) is the earnings response coefficient obtained assuming an IAR (AR) model for IBED. a refers to the slope of one period lagged earnings variable in regression equation (2.17).

[2]For each group, median values of $Z(t_a|\ell=5)$, a, $\Phi^i(I)$, and α^i_1 are reported. r(P) (r(S)) refers to Pearson (Spearman) correlation coefficient between $\Phi^i(I)$ and α^i_1.

[3]For each group, median values of $Z(t_a|\ell=5)$, a, $\Phi^s(I)$, and α^s_1 are reported. r(P) (r(S)) refers to Pearson (Spearman) correlation coefficient between $\Phi^s(I)$ and α^s_1.

coefficients are excluded. There is a 59% increase in Spearman correlation for the IAR model compared with a 20% increase for the AR model. It is evident from Table 2.8 that the Spearman correlation between earnings persistence and the earnings response coefficient for the IAR model is statistically significant at the 0.01 level for three out of four groups compared with only one group in Table 2.6. For the AR model, the Spearman correlation between earnings persistence and the earnings response coefficient is significant for all four groups. The Spearman correlations for the first three groups are consistent with hypothesis H_8, while that for Group 4 is not.

The results in Table 2.8 support hypothesis H_9. With the exception of Group 1, the Spearman correlations using the AR model are greater than those of the IAR model. Thus, even after controlling for measurement error in the earnings response coefficient, the unit root assumption is descriptive only for Group 1.

2.4.6 <u>Regression of Earnings Response Coefficient on Earnings Persistence and the Probability of a Unit Root in Earnings</u>

In the analysis reported in Table 2.6, firms were assigned to groups based on the probability of a unit root in earnings. The correlation analysis by groups sheds light on the impact of nonstationarity on the association between earnings persistence and the earnings response coefficient. The explanatory power of the regression model (equation (2.18)) could be increased by including the probability of a unit root as an independent variable. Specifically, the following regression model is estimated for the overall sample and for all four groups:[16]

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[16]In addition to including the interaction term, I considered the unit root statistic (i.e., $Z(t_a|\ell=5)$) as a main effect yielding no significant improvement in the explanatory power of the regression model.

$$\alpha_{1i} = \gamma_0 + \gamma_1 \cdot \Phi_i(I) + \gamma_2 \cdot \Phi_i(I) \cdot Z(t_a | \ell{-}5) + \nu_i \qquad (2.19)$$

where $\alpha_{1i} = \alpha^i_{1i}$ or α^s_{1i}, $\Phi_i(I) = \Phi^i_i(I)$ or $\Phi^s_i(I)$, and $Z(t_a | \ell{-}5)$ is the unit root statistic.

I include the interaction term since the bias in earnings persi- ence could be a function of the probability of a unit root. The regression results are reported in Table 2.9. There is a significant improvement in R^2 for regression model (2.19) relative to (2.18) (see Table 2.4). For the IAR model, there is an 83% increase in R^2 whereas for the AR model there is more than a two-fold increase in R^2.

Comparing the group-wise analysis in Table 2.6 versus Table 2.9, there is a marked improvement in R^2 for Groups 1,2, and 4 for both the AR and IAR models. For the IAR model, R^2 increased 24% to 53% for Group 1. The greatest increase in R^2 for the IAR model occurs for Group 1, which has the highest probability of a unit root. This is expected given that the largest change in earnings persistence occurs between a unit root and a near unit root series. For instance, consider the AR(1) process in (2.14). The persistence of this series for the ρ_1 values of 1.00, 0.90, and 0.80 is 11.00, 5.50, and 3.67 respectively. (I assume a discount rate of ten percent, see Table 2.1). For a decrease in ρ_1 from 1.00 to 0.90, earnings persistence decreases from 11.00 to 5.50, whereas for a similar decrease in ρ_1 from 0.90 to 0.80, earnings persistence decreases from 5.50 to 3.67. Since the probability of a near unit root is higher for Group 1, the incremental explanatory power of the interaction term is higher for Group 1.

For the AR model, while R^2 for Group 1 more than quadrupled, the R^2 for Group 2 increased by only 26%. Since I expect high measurement error in earnings persistence for Group 1, it is not surprising that the

Table 2.9
REGRESSION OF EARNINGS RESPONSE COEFFICIENT ON EARNINGS PERSISTENCE AND THE PROBABILITY OF UNIT ROOT IN IBED[1]

Panel A: Regression Results for the IAR(5) Model

$$\alpha^{i}_{1i} = \gamma_0 + \gamma_1 \cdot \Phi_i(I) + \gamma_2 \cdot \Phi_i(I) \cdot Z(t_a | \ell=5) + \nu_i$$

Sample	n	γ^i_0	γ^i_1	γ^i_2	F-Ratio	R^2
All Firms	449	3.844c	0.085a	0.188c	258.240c	0.537
		(5.670)	(1.730)	(15.300)		
Group 1	111	3.193a	0.050	0.220c	60.500c	0.528
		(1.560)	(0.420)	(8.130)		
Group 2	113	2.602b	0.108	0.150b	1.730	0.031
		(2.260)	(0.980)	(1.860)		
Group 3	113	1.281	−0.120	−0.078	0.110	0.002
		(1.080)	(−0.370)	(−0.450)		
Group 4	112	1.047	0.114	0.051b	1.800	0.032
		(1.230)	(0.910)	(1.870)		

Panel B: Regression Results for the AR(5) Model

$$\alpha_{1i} = \gamma_0 + \gamma_1 \cdot \Phi_i(I) + \gamma_2 \cdot \Phi_i(I) \cdot Z(t_a | \ell=5) + \nu_i$$

Sample	n	γ^s_0	γ^s_1	γ^s_2	F-Ratio	R^2
All Firms	449	0.948c	0.992c	0.372c	195.560c	0.467
		(2.990)	(12.230)	(16.410)		
Group 1	111	1.027	0.854c	0.524c	30.770c	0.363
		(0.740)	(2.540)	(6.870)		
Group 2	113	−0.679	1.290c	0.406c	19.870c	0.265
		(−1.080)	(5.710)	(2.890)		
Group 3	113	0.108	0.294	−0.078	5.100c	0.085
		(0.190)	(0.470)	(−0.240)		
Group 4	112	1.068c	0.316a	0.127b	2.530a	0.044
		(3.070)	(1.500)	(2.240)		

[1]A 'c' (b/a) indicates statistical significance at the 0.01 (0.05/0.10) level, one-tailed tests. The number in parentheses refers to t-statistic. 'n' refers to the number of firms in each sample. $\Phi^i(I)$ ($\Phi^s(I)$) is the estimate of earnings persistence from the IAR (AR) model for IBED, assuming a discount rate of 10%. α^i_1 (α^s_1) is the earnings response coefficient obtained assuming an IAR (AR) model for IBED. $Z(t_a | \ell=5)$ is the unit root test statistic.

interaction term dramatically increases the model's explanatory power.[17] Overall, the inclusion of both earnings persistence and an interaction term in the model explains about 50% of the variability in the earnings response coefficient for both IAR and AR models.

2.4.7 Strength of Price-Earnings Relationship as a Function of the Probability of a Unit Root

Panels A and B of Table 2.10 provide descriptive information on the price-earnings regression for all four groups for the IAR and AR models respectively. A priori there is no expectation regarding the strength of the price-earnings relation and the probability of a unit root in earnings. However, the results in Table 2.10 suggest that the higher the probability of a unit root in earnings, the stronger the price-earnings relation. This phenomenon is observed both for the IAR and AR models. Panel A shows that the median R^2 of the price-earnings regression decreases from 10.1% in Group 1 to 4.4% in Group 4. Similarly, the median p-value of 0.037 for Group 1 compares with 0.270 for Group 4. The price-earnings relation is statistically significant at the 0.05 level for 54.05% of the firms in Group 1 versus 24.11% in Group 4.

The results for the AR model in panel B exhibit a similar trend. The median R^2 of the price-earnings regression for Group 1 is 29.4% — more than seven times the median R^2 of 4.1% for Group 4. The price-earnings relation for the median firm is significant at the 0.001 level for Group 1 versus the 0.041 level for Group 4. Similarly, the earnings response coefficient is significant at the 0.05 level for 76.58% of firms in Group

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[17] I replicate the analysis after excluding firms with negative earnings response coefficients. Except for Group 3, the R^2 for the groups are very similar to those shown in Table 2.12. For Group 3, there is significant improvement in R^2 from 0.2% (8.5%) to 4.3% (19.4%) for the IAR (AR) model.

Table 2.10
DESCRIPTIVE INFORMATION ON PRICE-EARNINGS REGRESSION MODEL FOR FIRMS GROUPED BY THE PROBABILITY OF A UNIT ROOT[1]

Panel A: IAR(5) Model[2]

Variable	Mean	Minimum	First Quartile	Median	Third Quartile	Maximum	% Sig
Group 1 (n=111):							
N	32.568	18.000	28.000	35.000	36.000	37.000	
α^i_1	9.113	-6.595	1.685	4.570	12.902	62.760	54.05
$t(\alpha^i_1)$	1.913	-3.242	0.703	1.849	3.064	9.635	
p-value	0.179	0.000	0.003	0.037	0.245	0.999	
R^2	0.152	0.000	0.025	0.101	0.236	0.732	
Group 2 (n=113):							
N	31.664	18.000	27.000	35.000	36.000	37.000	
α^i_1	1.919	-7.575	-0.108	1.207	3.981	15.532	30.97
$t(\alpha^i_1)$	0.912	-6.889	-0.060	0.847	1.882	6.447	
p-value	0.309	0.000	0.034	0.203	0.524	0.999	
R^2	0.090	0.000	0.009	0.048	0.120	0.674	
Group 3 (n=113):							
N	32.336	17.000	27.500	35.000	36.000	37.000	
α^i_1	1.620	-5.429	-0.195	0.992	2.179	13.014	30.97
$t(\alpha^i_1)$	1.126	-3.332	-0.244	0.964	1.881	7.371	
p-value	0.310	0.000	0.035	0.172	0.595	0.999	
R^2	0.100	0.000	0.012	0.048	0.107	0.633	
Group 4 (n=112):							
N	32.402	16.000	28.250	36.000	36.000	37.000	
α^i_1	0.598	-7.990	-0.264	0.442	1.242	8.649	24.11
$t(\alpha^i_1)$	0.641	-3.230	-0.380	0.620	1.668	4.993	
p-value	0.354	0.000	0.054	0.270	0.647	0.999	
R^2	0.089	0.000	0.008	0.044	0.108	0.455	

Panel B: AR(5) Model[3]

Variable	Mean	Minimum	First Quartile	Median	Third Quartile	Maximum	% Sig
Group 1 (n=111):							
N	33.234	19.000	28.000	36.000	37.000	38.000	
α^s_1	6.460	-1.030	3.008	5.361	9.553	22.058	76.58
$t(\alpha^s_1)$	3.433	-1.853	1.731	3.632	4.846	9.950	
p-value	0.078	0.000	0.000	0.001	0.046	0.964	
R^2	0.283	0.000	0.089	0.294	0.417	0.739	

Table 2.10 (Cont'd.).

Panel B (Cont'd.).

Variable	Mean	Minimum	First Quartile	Median	Third Quartile	Maximum	% Sig
Group 2 (n=113):							
N	32.416	19.000	27.000	36.000	37.000	38.000	
α^{s}_{1}	2.753	-3.746	0.548	2.427	4.484	12.657	53.10
$t(\alpha^{s}_{1})$	1.789	-3.251	0.580	1.807	3.016	5.610	
p-value	0.185	0.000	0.003	0.042	0.283	0.998	
R^2	0.141	0.000	0.019	0.119	0.221	0.557	
Group 3 (n=113):							
N	33.115	18.000	28.000	36.000	37.000	38.000	
α^{s}_{1}	1.730	-3.423	0.019	1.264	2.837	15.385	42.48
$t(\alpha^{s}_{1})$	1.310	-1.597	0.029	1.241	2.347	6.164	
p-value	0.252	0.000	0.013	0.113	0.489	0.940	
R^2	0.097	0.000	0.012	0.063	0.141	0.528	
Group 4 (n=112):							
N	33.161	17.000	28.250	37.000	37.000	38.000	
α^{s}_{1}	0.782	-4.061	-0.093	0.647	1.362	7.478	25.90
$t(\alpha^{s}_{1})$	0.861	-3.845	-0.218	0.954	1.715	5.753	
p-value	0.319	0.000	0.049	0.173	0.585	0.999	
R^2	0.078	0.000	0.014	0.041	0.098	0.562	

[1]Firms are assigned to the four groups based on descending values of $Z(t_a|\ell=5)$, the unit root test statistic. 'n' refers to the number of firms in each group.

[2]α^{i}_{1}, $t(\alpha^{i}_{1})$, and R^2 are the slope coefficient (or the earnings response coefficient), t-statistic of the slope coefficient, and the coefficient of determination, from the regression of change in equity value on earnings innovation from the IAR process (see equation (2.11)), and 'p-value' refers to the probability of observing a value less than $t(\alpha^{i}_{1})$ from the t-distribution . '% Sig' refers to the percentage of firms for which the price-earnings relation is significant at the 0.05 level (one-tailed). 'N' refers to the number of observations used in estimating the price-earnings relation.

[3]α^{s}_{1}, $t(\alpha^{s}_{1})$, and R^2 are the slope coefficient (or the earnings response coefficient), t-statistic of the slope coefficient, and the coefficient of determination, from the regression of change in equity value on earnings innovation from the AR process (see equation (2.11)), and 'p-value' refers to the probability of observing a value less than $t(\alpha^{s}_{1})$ from the t-distribution . '% Sig' refers to the percentage of firms for which the price-earnings relation is significant at the 0.05 level (one-tailed). 'N' refers to the number of observations used in estimating the price-earnings relation.

1 compared with 25.9% for Group 4.

While the monotonic decline in the strength of the price-earnings relation is evident for both AR and IAR models, the AR model outperforms the IAR model for all four groups. The difference between the two models is more pronounced in groups 1-3. Based on a p-value of 0.05, there are 22.53, 22.13, and 11.51 percent more firms in Groups 1,2, and 3 respectively for which the price-earnings relation is statistically significant for the AR model compared with the IAR model. Note that firms for which the IAR model is more appropriate in computing earnings persistence (Group 1), the AR model is better in terms of the strength of the price-earnings relation. Overall, the higher the earnings persistence, the lower the measurement error in earnings innovations, and consequently, the stronger the price-earnings relation. This is because, the higher the persistence, the higher the importance of past values in predicting current earnings. This implies that firms with high persistence have predictable earnings, and consequently, yield lower measurement error in earnings innovations.

2.4.8 Comparison of the Random Walk Model with Firm-Specific Time-Series Models

Watts and Zimmerman [1986, p. 152] conclude that "annual earnings are well described by a random walk process." Lorek, Kee and Vass [1981, p. 110] conclude that: "We interpret the relatively good performance of the submartingale (random walk with "drift") vis-a-vis the Box-Jenkins model for annual earnings as a reflection of the state of the art in time-series methodology rather than supportive evidence for the submartingle process." To shed some light on this question, I compare the random walk model with firm-specific time-series models in terms of the strength of the price-earnings relation. Table 2.11 provides the results of price-earnings regressions where earnings are assumed to follow a random walk. In this case, unexpected earnings is computed as current period IBED minus the prior period IBED. The earnings response coefficient estimate from the random walk model is denoted by $\alpha^r{}_1$.

Comparing the random walk model with both the AR and IAR models (Table 2.11 versus Table 2.3) for the total sample, it is evident that the random walk model lies somewhere in between the AR and IAR models in terms of the strength of the price-earnings relation. For the random walk model, the price-earnings regression is significant at the 0.05 level for 41.87% of the firms compared with 49.44% (34.97%) for the AR (IAR) models. Similarly, the median p-value for the random walk model is 0.108 compared with 0.053 (0.147) for the AR (IAR) model. The results by groups are generally consistent with those of the total sample. For the first three groups, the random walk model yields a stronger (weaker) price-earnings relation compared with the IAR (AR) model (Table 2.11 versus Table 2.10). For Group 4, all three models are poor fits. If simplicity of the expectations model is an important criterion, then the random walk model may be adequate. However, the assumption of a unit root for all firms, via a random walk process or an IAR model, may be inappropriate for estimating earnings persistence <u>and</u> understates the price-earnings relation.

2.4.9 Earnings Predictability as a Determinant of the Association Between Earnings Persistence and Earnings Response Coefficient

If persistence and predictability are highly correlated, then each may act as a proxy for the other. Thus, the "so-called" effects of nonstationarity in earnings could be driven by differences in

Table 2.11
DESCRIPTIVE INFORMATION ON PRICE-EARNINGS REGRESSION
ASSUMING A RANDOM WALK MODEL FOR IBED[1]

Variable	Mean	Minimum	First Quartile	Median	Third Quartile	Maximum	% Sig
All Firms (n=449):							
α^r_1	3.372	-8.904	0.042	1.288	4.480	52.978	41.87
$t(\alpha^r_1)$	1.424	-6.584	0.054	1.267	2.619	10.702	
p-value	0.266	0.000	0.007	0.108	0.479	0.999	
R^2	0.130	0.000	0.016	0.072	0.194	0.771	
Group 1 (n=111):							
α^r_1	9.190	-8.094	1.897	6.178	14.697	52.978	68.47
$t(\alpha^r_1)$	2.728	-3.447	0.951	2.622	4.408	10.702	
p-value	0.143	0.000	0.000	0.007	0.174	0.999	
R^2	0.230	0.000	0.058	0.204	0.365	0.771	
Group 2 (n=113):							
α^r_1	2.342	-7.022	-0.058	1.558	5.059	15.098	39.82
$t(\alpha^r_1)$	1.146	-6.584	-0.047	1.184	2.442	6.447	
p-value	0.271	0.000	0.010	0.123	0.518	0.999	
R^2	0.111	0.000	0.011	0.070	0.173	0.653	
Group 3 (n=113):							
α^r_1	1.474	-7.012	-0.189	1.011	2.505	13.092	32.74
$t(\alpha^r_1)$	1.085	-4.177	-0.218	0.895	2.010	7.371	
p-value	0.310	0.000	0.028	0.190	0.585	0.999	
R^2	0.103	0.000	0.014	0.048	0.124	0.657	
Group 4 (n=112):							
α^r_1	0.558	-7.237	-0.245	0.500	1.114	8.649	26.79
$t(\alpha^r_1)$	0.756	-2.780	-0.436	0.734	1.833	5.632	
p-value	0.339	0.000	0.040	0.235	0.667	0.996	
R^2	0.079	0.000	0.011	0.048	0.116	0.569	

[1]Firms are assigned to the four groups based on descending values of $Z(t_a|\ell=5)$, the unit root test statistic. 'n' refers to the number of firms in each group. α^r_1, $t(\alpha^r_1)$, and R^2 are the slope coefficient (or the earnings response coefficient), t-statistic of the slope coefficient, and the coefficient of determination, from the regression of change in equity value on change in earnings, and 'p-value' refers to the probability of observing a value less than $t(\alpha^r_1)$ from the t-distribution . '% Sig' refers to the percentage of firms for which the price-earnings relation is significant at the 0.05 level (one-tailed). 'N' refers to the number of observations used in estimating the price-earnings relation.

predictability across firms. For example, Lipe [1990] found a significant negative association between the earnings response coefficient and the inverse of earnings predictability. Lipe's findings in association with mine suggest that firms with a high earnings response coefficient have predictable and persistent earnings, and consequently, have nonstationary earnings series. In order to disentangle the effects of persistence and predictability, I replicate my earlier test after controlling for differences in earnings predictability. The coefficient of variation in earnings innovation (CV) is chosen as a proxy for (inverse of) predictability. CV is computed as follows:[18]

$$CV(\epsilon_t) = \sigma(\epsilon_t)/|\rho_0| \tag{2.20}$$

where ϵ_t and ρ_0 are obtained from equation (2.2) for the IAR model and from equation (2.3) for the AR model. $|\cdot|$ is the absolute value operator. The two measures of CV, one based on the IAR model and the other on the AR model, are denoted by $CV(\epsilon^i{}_t)$ and $CV(\epsilon^s{}_t)$ respectively. The Spearman correlation between the earnings response coefficient and CV for the IAR (AR) model is −0.383 (−0.337) which is significant at the 0.01 (0.01) level. This evidence is consistent with the findings of Lipe [1990, Table 3].[19]

Firms are sorted by CV in descending order. Using the quartiles of CV, firms are assigned to four groups with firms in Group 1 (Group 4)

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[18]Since the time-series models are estimated on undeflated IBED, the cross-sectional differences in $\sigma(\epsilon_t)$ could be due to differences in earnings levels. In order to control for differences in earnings levels, the standard deviation in earnings innovation ($\sigma(\epsilon_t)$) is deflated by the absolute value of intercept (ρ_0) of the autoregressive model.

[19]My predictability measure is similar to that of Lipe's [1990]. However, Lipe reports Kendall Partial Rank correlation (after controlling for differences in persistence) instead of the Spearman correlation reported in this study.

having the lowest (highest) predictability of earnings. The analysis (in Table 2.4) is replicated for all groups separately, and the results are reported in Table 2.12. Panels A and B provide the median values of $CV(\epsilon_t)$, $Z(t_a|\ell=5)$, $\Phi(I)$, and α_1 of the four groups for the IAR and AR models respectively.[20] Pearson and Spearman correlations between earnings persistence and earnings response coefficients are also reported.

Based on the median values reported in Panel A, firms with high (low) predictable earnings tend to have a high (low) probability of a unit root. Similarly, the median value of earnings persistence (earnings response coefficient) increases from 6.940 (0.620) for the low predictability group to 17.100 (5.324) for the high predictability group. The reported correlations suggest that predictability of earnings is not driving the association between earnings persistence and the earnings response coefficient for the IAR model. While the highest correlation is found for the highest predictable earnings group, there is no monotonic increase in correlation from Group 1 to Group 4.

Similar to panel A, the median values in panel B suggest that firms with high (low) predictable earnings tend to have high (low) earnings persistence. Again, there is no monotonic association between earnings predictability and the earnings response coefficient or the probability of a unit root in earnings. Thus, there is no evidence that earnings predictability drives the results for the AR model. The two highest correlations for the AR model pertain to Groups 3 and 2, groups with

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[20]The magnitude of $CV(\epsilon_t)$ is not comparable across the IAR and AR models. The denominator of $CV(\epsilon^i_t)$, ρ^i_0, is an estimate of the mean of differenced earnings series where as the denominator of $CV(\epsilon^s_t)$, ρ^s_0, is an estimate of the mean of level earnings series. The former is, in general, smaller in magnitude resulting in CV of the IAR model larger in magnitude compared with that of the AR model.

Table 2.12
CORRELATION BETWEEN EARNINGS PERSISTENCE AND EARNINGS RESPONSE COEFFICIENT OF FIRMS GROUPED BY EARNINGS PREDICTABILITY[1]

Panel A: Correlations for the IAR(5) Model[2]

Group	n	$CV(\epsilon^i_t)$	$Z(t_a \mid \ell=5)$	$\Phi^i(I)$	α^i_1	$r^i(P)$	$r^i(S)$
1	112	43.638	-2.413	6.940	0.620	0.288c	0.179b
2	112	10.016	-2.111	7.767	0.660	-0.128a	-0.153a
3	113	4.196	-1.365	9.301	1.808	0.244c	0.178b
4	112	1.745	0.137	17.100	5.324	0.419c	0.278c

Panel B: Correlations for the AR(5) Model[3]

Group	n	$CV(\epsilon^s_t)$	$Z(t_a \mid \ell=5)$	$\Phi^s(I)$	α^s_1	$r^s(P)$	$r^s(S)$
1	112	1.982	-2.401	1.603	0.621	0.191b	0.137a
2	112	0.831	-1.905	2.579	1.583	0.498c	0.499c
3	113	0.549	-0.695	4.486	3.483	0.379c	0.522c
4	112	0.385	-1.547	5.350	3.090	0.172b	0.181b

[1]A "c" (b/a) indicates statistical significance at the 0.01 (0.05/0.10) level, one-tailed tests. 'n' refers to the number of firms in each group. $\Phi^i(I)$ ($\Phi^s(I)$) is the estimate of earnings persistence from the IAR (AR) model for IBED, assuming a discount rate of 10%. α^i_1 (α^s_1) is the earnings response coefficient obtained assuming an IAR (AR) model for IBED. $Z(t_a \mid \ell=5)$ is the unit root test statistic.

[2]Firms are assigned to the four groups based on descending values of $CV(\epsilon^i_t)$, the coefficient of variation of earnings innovation from the IAR(5) model. For each group, median values of $CV(\epsilon^i_t)$, $Z(t_a \mid \ell=5)$, $\Phi^i(I)$, and α^i_1 are reported. $r^i(P)$ ($r^i(S)$) refers to Pearson (Spearman) correlation coefficient between $\Phi^i(I)$ and α^i_1.

[3]Firms are assigned to the four groups based on descending values of $CV(\epsilon^s_t)$, the coefficient of variation of earnings innovation from the AR(5) model. For each group, median values of $CV(\epsilon^s_t)$, $Z(t_a \mid \ell=5)$, $\Phi^s(I)$, and α^s_1 are reported. $r^s(P)$ ($r^s(S)$) refers to Pearson (Spearman) correlation coefficient between $\Phi^s(I)$ and α^s_1.

"medium" earnings predictability. The groups with the highest and lowest earnings predictability have similar correlations suggesting that the effects of earnings predictability are not confounding the effects of nonstationarity on the association between earnings persistence and earnings response coefficients.

This analysis is repeated for each of the 16 sub-groups formed by four levels of $Z(t_a|\ell-5)$ and four levels of CV. The Spearman correlation, along with the number of firms in each sub-group, is reported for the IAR and AR models in panels A and B of Table 2.13. The correlation is reported only for sub-groups with at least ten observations. The distribution of firms in panel A suggests an association between earnings predictability and the probability of a unit root for the IAR model. For example, among the 111 (112) firms in the group with the highest (lowest) probability of a unit root 92% (89%) of them fall into the two highest (lowest) earnings predictability groups. In addition, the correlation between earnings persistence and the earnings response coefficient for Group 1 of $Z(t_a|\ell-5)$ (see Table 2.6) is primarily driven by firms in the sub-group with the highest earnings predictability. For the other sub-groups, there is no systematic pattern to explain the distribution of correlations. Thus, for the IAR model, this sub-group analysis suggests that the effects of earnings predictability and earnings nonstationarity are dependent.

The distribution of sample firms in panel B suggests that there is a weak association between earnings predictability (for the AR model) and the probability of a unit root. However, the association is not monotonic. For example, 60% of the firms in Group 1 of $Z(t_a|\ell-5)$, compared with 72% of the firms in Group 2 of $Z(t_a|\ell-5)$, fall into the two highest

Table 2.13
CORRELATION BETWEEN EARNINGS PERSISTENCE AND EARNINGS RESPONSE COEFFICIENT FOR FIRMS GROUPED BY LEVELS OF EARNINGS PREDICTABILITY AND PROBABILITY OF A UNIT ROOT IN EARNINGS[1]

Panel A: IAR(5) Model

		$CV(\epsilon^i_t)$ High 1	Medium High 2	Medium Low 3	Low 4
$Z(t_a \mid \ell=5)$ High	1	1 (N/A)	8 (N/A)	31 (−0.021)	71 (0.223)b
Medium High	2	12 (−0.270)	23 (−0.469)b	40 (0.189)	38 (−0.178)
Medium Low	3	46 (0.242)a	34 (−0.239)a	30 (0.183)	3 (N/A)
Low	4	53 (0.012)	47 (0.135)	12 (−0.455)a	0 (N/A)

Panel B: AR(5) Model

		$CV(\epsilon^a_t)$ High 1	Medium High 2	Medium Low 3	Low 4
$Z(t_a \mid \ell=5)$ High	1	12 (0.196)	32 (0.289)a	52 (0.303)b	15 (0.275)
Medium High	2	19 (0.186)	13 (0.082)	28 (0.615)c	53 (0.243)b
Medium Low	3	29 (0.016)	31 (0.519)c	18 (0.373)a	35 (0.210)
Low	4	52 (0.189)a	36 (−0.022)	15 (0.564)b	9 (N/A)

[1]The numbers given in the table refer to numbers of firms in each sub group. The numbers in parentheses refer to Spearman correlation between earnings persistence and earnings response coefficient for each group. The Spearman correlation is reported only for sub groups with at least ten firms. A 'c' (b/a) indicates statistical significance at the 0.01 (0.05/0.10) level, one-tailed tests. $Z(t_a \mid \ell=5)$ is the unit root test statistic. $CV(\epsilon^i_t)$ ($CV(\epsilon^a_t)$) is the coefficient of variation of earnings innovation from the IAR (AR) model. $CV(\epsilon_t)$ is the measure of (inverse of) earnings predictability.

predictability groups. Although the association is not apparent for Groups 1 and 2 of $Z(t_a|\ell=5)$, it is evident for Groups 3 and 4 of $Z(t_a|\ell=5)$. For example, 79% of the firms in Group 4 of $Z(t_a|\ell=5)$, compared with only 53% of the firms in Group 3 of $Z(t_a|\ell=5)$, fall into the two lowest predictability groups.

The analysis in panel B suggests that earnings predictability is not confounding the effects of earnings nonstationarity. Six of the eight significant correlations pertain to the two groups with "medium" earnings predictability (i.e., Groups 2 and 3) whereas only one significant correlation pertains to the group with the highest earnings predictability. In terms of magnitude, the correlation obtained for the one sub-group with the highest earnings predictability ranks seventh out of eight sub-groups. Thus, the results in Table 2.13 suggest that earnings nonstationarity significantly affects the association between earnings persistence and the earnings response coefficient.

Chapter Three

INTER-TEMPORAL INSTABILITY IN EARNINGS RESPONSE COEFFICIENTS

In this chapter I investigate how measurement error in unexpected earnings (value-relevant transitory components as well as value-irrelevant noise) contributes to the bias and inter-temporal instability in the earnings response coefficients.

3.1 SPECIFICATION OF THE PRICE-EARNINGS RELATION

3.1.1 Unexpected Earnings Measured Without Error

Using the framework of Kormendi and Lipe [1987], consider the following linear price-earnings model:

$$y_{it} = x_{it}\alpha_i + \epsilon_{it} \tag{3.1}$$

$t = 1,\ldots,T$ (number of time-series observations)

$i = 1,\ldots,N$ (number of firms)

where y_{it} is a measure of abnormal returns, x_{it} is the unexpected earnings, α_i is the ERC of firm i, and ϵ_{it} is the part of abnormal returns unexplained by the unexpected earnings with $E(\epsilon_{it}) = 0$ for all i and t.[1]

However, in a typical cross-sectional study, a single cross-sectional ERC is estimated at time $t=\tau$, i.e., the following regression is conducted:

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[1]Alternatively, the true model could have raw returns as the dependent variable and market return and unexpected earnings as the two independent variables. In such case, the model (3.2) induces an estimation bias in the ERC estimate since the market model residuals are regressed on the unexpected earnings (see Goldberger and Jochems [1961] and Beaver [1987]). However, Ramesh and Thiagarajan [1989] document that this bias from the two-stage approach is trivial since there is very low correlation between market returns and unexpected earnings.

$$y_{i\tau} = x_{i\tau}\hat{\alpha}_{\tau} + \hat{\epsilon}_{i\tau} \tag{3.2}$$

$i = 1,\ldots,N$ (number of firms)

where $\hat{\alpha}_{\tau}$ is the OLS estimate of cross-sectional ERC and $\hat{\epsilon}_{i\tau}$ is the regression residual. To link the cross-sectional and firm-specific ERCs, consider the probability limit of $\hat{\alpha}_{\tau}$:[2]

$$\text{plim}(\hat{\alpha}_{\tau}) = \frac{\sum_i x^2_{i\tau}\alpha_i}{\sum_i x^2_{i\tau}} \tag{3.3}$$

This expression indicates that, given model (3.1), the expected value of the cross-sectional ERC is a weighted average of the firm-specific ERCs with weights being the squared values of the unexpected earnings in the estimation period τ. Equation (3.3) provides several insights into the price earnings relation.

First, the expression clearly links the firm-specific ERCs and the cross-sectional ERC. Second, the weights given to the firm-specific ERCs are determined only by the magnitude of unexpected earnings in the estimation period. Specifically, the ERC of firms with larger magnitudes of unexpected earnings (both positive and negative) in the estimation period are given disproportionately larger weights. Third, expression (3.3) indicates that the cross-sectional distribution of unexpected earnings in the estimation period determines the variability in the cross-sectional response coefficient. which suggests that inter-temporal

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[2]Note that $\hat{\alpha}_{\tau}$ equals $(x_{i\tau}'x_{i\tau})^{-1}(x_{i\tau}'y_{i\tau})$. Substituting for $y_{i\tau}$ from (3.1) and taking probability limits, I obtain (3.3). If one considers the correlation between unexpected earnings and market return, an additional term capturing the effect of this correlation should be added to (3.3) (see Ramesh and Thiagarajan [1989, equation (13)]).

variation in the weights results in inter-temporal variation in the response coefficient. Thus, even under ideal conditions (no measurement error in unexpected earnings and conformity of the actual relation to the assumed linear relation), inter-temporal variation in the cross-sectional ERC is unavoidable.[3]

3.1.2 Unexpected Earnings Measured with Error

Equation (3.3) suggests that the cross-sectional unexpected earnings variability impacts the magnitude of the cross-sectional ERC. To address if such variability can explain (a) the significant inter-temporal instability of the observed ERCs and (b) the low magnitude of the observed cross-sectional ERCs, I consider the scenario where unexpected earnings are measured with error.

Consider

$$x^*_{it} = x_{it} + \xi_{it} \tag{3.4}$$

where x^*_{it} and ξ_{it} are the observed unexpected earnings and measurement error respectively, and both y_{it} and x_{it} are uncorrelated with ξ_{it}.

Now consider the following regression model:

$$y_{i\tau} = x^*_{i\tau}\alpha^*_\tau + \epsilon^*_{i\tau} \tag{3.5}$$

where α^*_τ is the OLS estimate of cross-sectional ERC from regressing stock returns on the unexpected earnings measured with error, and $\epsilon^*_{i\tau}$ is the regression residual. Standard econometric results indicate that measurement error in the independent variable downward biases the slope coefficient (e.g., see Schmidt [1976, p. 106]). To see this in the present context, consider the probability limit of α^*_τ:

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[3]The absence of inter-temporal variability in weights is theoretically possible but unlikely in practice.

$$\text{plim}(\alpha^*_\tau) = \frac{\text{plim}(\hat{\alpha}_\tau)}{1 + (\sigma^2(\xi_\tau)/\sigma^2(x_\tau))} \qquad (3.6)$$

where $\sigma^2(\xi_\tau)$ ($\sigma^2(x_\tau)$) is the cross-sectional variance of measurement error (true unexpected earnings).

It is evident from (3.6) that the downward bias in the cross-sectional ERC is a function of the ratio of cross-sectional noise variance to signal variance (i.e., $\sigma^2(\xi_\tau)/\sigma^2(x_\tau)$). In addition, inter-temporal variation in the noise to signal ratio can introduce additional instability in the observed ERCs.

3.1.3 The Effect of Value Relevant Transitory Elements

The analysis so far assumes that ξ_{it} is pure measurement error in the sense that it is not value relevant. A more realistic scenario is to model the unexpected earnings proxy as consisting of a value relevant transitory component and a pure measurement error in addition to a value relevant permanent component. To illustrate this, consider the following process for observed earnings (E_{it}):[4]

$$E_{it} = U_{it} + \pi_{it} \qquad (3.7)$$

where U_{it} and π_{it} are the value relevant permanent and transitory elements in earnings in the sense that

$$U_{it} = U_{it-1} + u_{it} \qquad (3.8)$$

and

$$y_{it} = u_{it}\alpha_i + \pi_{it} + \epsilon_{it} \qquad (3.9)$$

where π_{it} and u_{it} are uncorrelated white noise processes, and other

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[4]This earnings process is consistent with Model III of Ohlson (1988) where stock-return is a function of current earnings level and earnings change. See Ramesh and Thiagarajan (1991) for an illustration of this point.

variables as defined in (3.1).[5] Within Kormendi and Lipe's [1987] framework, α_i is the persistence of a random walk process and is equal to (1+r/r) where 'r' is the firm-specific discount rate. Note that the slope coefficient of π_{it} is one since the transitory components are assumed to have a dollar-for-dollar effect on prices.[6] Now consider change in earnings (ΔE_{it}), a popular measure for unexpected earnings in the extant research:

$$\Delta E_{it} = u_{it} + \pi_{it} - \pi_{it-1} \tag{3.10}$$

where u_{it} (π_{it}) is the unexpected permanent (transitory) component in earnings and π_{it-1}, the lagged transitory component, is the measurement error. Now consider the cross-sectional regression of stock returns on change in earnings:[7]

$$y_{i\tau} = \Delta E_{i\tau}\hat{\alpha}^*_\tau + \hat{\epsilon}^*_{i\tau} \tag{3.11}$$

where $\hat{\alpha}^*_\tau$ is the OLS estimate of cross-sectional ERC from regressing stock returns on the change in earnings, and $\hat{\epsilon}_{i\tau}$ is the regression residual. To see the effect of both the transitory element and measurement error on the

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[5]The intercept term in the earnings process is suppressed for notational simplicity.

[6]The earnings process (3.7) is chosen only as an illustration. For example, if u_{it} and π_{it} are positively (negatively) correlated, then the permanent component of earnings has a persistence greater (smaller) than that of a random walk process. However, this correlation will not affect any inferences regarding the role of the transitory elements.

Kormendi and Lipe's [1987] valuation model also implicitly incorporates both permanent and transitory components in earnings except that the innovations in the two components are assumed to be perfectly correlated. This is because an ARIMA model reduces all unforeseen economic events into a single innovation, and the permanent and transitory components from the model are both based on this innovation (see Beveridge and Nelson [1981] and Stock and Watson [1988]).

[7]The deflator of unexpected earnings is suppressed for notational simplicity.

ERC estimate, consider the probability limit of $\hat{\alpha}^*_\tau$:[8]

$$\text{plim}(\hat{\alpha}^*_\tau) = \frac{(\sum_i u^2_{i\tau}\alpha_i)/(\sum_i u^2_{i\tau})}{1 + [(\sigma^2(\pi_\tau) + \sigma^2(\pi_{\tau-1}))/\sigma^2(u_\tau)]} \qquad (3.12)$$

where $\sigma^2(u_\tau)$ ($\sigma^2(\pi_\tau)$) is the cross-sectional variance of the unexpected component of the permanent (transitory) component of earnings at time τ.[9] Thus, both transitory elements ($\pi_{i\tau}$) and measurement error ($\pi_{i\tau-1}$) in earnings have the same effect on the estimate of ERC, i.e., a downward bias.[10]

The analysis so far suggests that (1) the extant research method induces an inherent variability in cross-sectional ERCs even in the absence of measurement error, (2) measurement error in unexpected earnings not only biases the ERC downwards, but also contributes to the inter-temporal variability of the ERCs, and (3) the effect of the value-relevant transitory element on the ERC estimate is similar to that of pure measurement error.

In the following section, I conduct empirical analyses to address two issues based on the framework developed in this section: (1) To what extent the extant research method contributes to intertemporal variability in ERCs? and (2) To what extent measurement error or transitory elements in earnings can explain the inter-temporal variability and the low

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[8]Here, I assume that the ERC is the stock market response to the unexpected component of the permanent earnings.

[9]The proof of this expression follows from (3.6) if one substitutes $\pi_{i\tau} - \pi_{i\tau-1}$ for $\xi_{i\tau}$ and $u_{i\tau}$ for $x_{i\tau}$.

[10]While the expression (3.12) depends on the assumption that $u_{i\tau}$ and $\pi_{i\tau}$ are uncorrelated, the thrust of the argument is unaffected by correlation between the two.

magnitude of observed ERCs?

3.2 EMPIRICAL RESULTS

3.2.1 Empirical Estimates of the Annual ERC

The sample for this study consists of 679 December fiscal-year firms with continuous data on stock returns and income before extraordinary items and discontinued operations (IBED) from 1967 to 1987.[11] To estimate cross-sectional ERC, the following regression model is conducted:

$$CAR_{i\tau} = \mu_\tau + \alpha_\tau UE_{i\tau} + e_{i\tau} \qquad (3.13)$$

where $CAR_{i\tau}$ is the cumulative abnormal stock return of firm i for the period $\tau-1$ to τ, and $UE_{i\tau}$ is a measure of unexpected earnings defined below:[12]

$$UE_{i\tau} = (IBED_{i\tau} - IBED_{i\tau-1})/P_{i\tau-1} \qquad (3.14)$$

where $P_{i\tau-1}$ is the stock price of firm i at time $\tau-1$.[13] The parameter estimates are denoted $\hat{\mu}_\tau$ and $\hat{\alpha}_\tau$.

Panel A of Table 3.1 provides the results of estimating model (3.13)

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[11]All Compustat firms that have December fiscal year ends and continuous data (from 1967 and 1987) on IBED, stock price (P), and dividends per share (DPS) are included in the sample. This results in a sample of 679 firms and 13,580 firm-years. All per-share numbers are adjusted for stock splits and stock dividends. Using P and DPS, annual raw returns (January to December) are computed.

[12]For each firm, a single market model regression is estimated across all years, and the residuals are treated as cumulative abnormal returns (CAR). The estimates of cross-sectional ERCs are qualitatively unaffected by the choice of return metric. I replicated Table 3.1 using raw return as the dependent variable, and the estimated ERCs from this regression are similar to those reported in Table 3.1.

[13]Unexpected earnings outside the range of +/- 1.00 are truncated at +/- 1.00.

both across all firm-years and separately for each year.[14] The annual regression results highlight the inter-temporal instability of the ERCs. Furthermore, to enable comparison of my results with prior work that overlaps the chosen sample-period, I provide in the last column of Panel A the ERC estimates from Rayburn's study [1986, Table 6].[15] Though Rayburn's ERC estimates are based on a much smaller sample, her reported magnitude of annual ERCs is quite similar to that of this study. In addition, ERC estimates in both studies exhibit a temporally declining trend.[16]

While unexpected earnings is highly significant in all regressions, the results in Table 3.1 indicate a high degree of intertemporal instability both in the magnitude of the ERCs and in the regression R^2. The ERC estimates (R^2) range from 0.316 (1.4%) to 2.778 (19.98%). The results of Chow tests of all pairs of the annual ERCs (see Panel B) reject the null hypothesis of intertemporal stability almost half the time at the 0.01 level.[17] In addition, the magnitude of cross-sectional ERCs is considerably low compared to empirically observed P/E ratios. These results strongly support Lev's [1989] concerns about the usefulness of price-earnings regression models to investors.

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[14]While firms have continuous data from 1967 onwards, the data for 1967 are used in computing the variables for 1968, which results in 20 annual regressions (1968 to 1987).

[15]Since Rayburn includes both change in cash flows and change in accruals in her regression model, the negative of the slope coefficient of her accruals variable ($-\beta_2$) is the ERC estimate (see Jennings [1990, p. 927] for an explanation).

[16]See Section 3.2.3 for a detailed investigation of this trend.

[17]Given 20 annual regressions, there are 190 (20!/(18!x2!)) unique pairs of ERCs.

Table 3.1
REGRESSION OF CUMULATIVE ABNORMAL RETURNS ON UNEXPECTED EARNINGS

Panel A: Parameter Estimates[1]

$$CAR_{i\tau} = \hat{\mu}_\tau + \hat{\alpha}_\tau UE_{i\tau} + e_{i\tau}$$

Year	$\hat{\mu}_\tau$	$\hat{\alpha}_\tau$	$t(\hat{\alpha}_\tau)$	R^2	$\hat{\alpha}$ (Rayburn)
ALL	-0.0079	0.7379	37.199	9.25	
68	0.1230	2.7777	10.715	14.50	4.9137
69	-0.0877	2.5022	7.101	6.93	2.4886
70	-0.0405	1.7450	8.633	9.92	1.6415
71	-0.0139	1.0937	6.919	6.60	1.3116
72	-0.0897	0.5693	3.102	1.40	1.6479
73	-0.0596	0.8147	5.717	4.61	1.2696
74	0.0237	0.7394	12.474	18.69	2.0665
75	0.0704	0.7815	11.126	15.46	0.4420
76	0.0698	0.9018	13.002	19.98	0.4145
77	0.0704	0.6772	8.170	8.97	0.6407
78	-0.0247	0.7558	7.925	8.49	0.6902
79	-0.0025	1.4624	11.758	16.96	0.4368
80	-0.1298	0.8119	8.307	9.25	0.4351
81	0.0737	0.7046	8.343	9.32	0.2466
82	0.0429	0.8407	10.486	13.97	0.1735
83	0.0306	0.7303	9.453	11.66	
84	-0.0652	0.3162	4.778	3.26	
85	-0.0608	0.3843	6.262	5.48	
86	-0.0633	0.5881	9.020	10.73	
87	-0.0626	0.5031	9.034	10.76	
Median		0.7686	8.488	9.62	

Panel B: Chow Tests of Difference in Coefficients

Rejection of null at chosen alpha levels 10%	5%	1%	Median F	Median P
62.11%	57.37%	48.42%	5.848	0.0157

[1]While the annual regressions are based on 679 observations, the pooled regression is based on 13,580 observations. All t-statistics are significant at the 0.01 level, one-tailed tests. CAR refers to cumulative market-model abnormal returns from January to December and UE refers to change in income before extraordinary items and discontinued operations per share divided by prior year's stock price.

3.2.2 A test of the Inherent Instability in the ERC Estimates

The analysis in Section 3.1 suggests that the extant research method leads to inherent variability in ERC estimates. If the true firm-specific ERCs are known, then the importance of this source of variability can be tested by correlating observed cross-sectional ERC with its theoretical value from equation (3.3). A strong association between the two would highlight the role of the weights in the estimate of the cross-sectional response coefficient and the resulting limitation of the extant research method to produce intertemporally stable ERCs. Since the true firm-specific ERCs are not known, I empirically estimate them using the following OLS regression model:[18]

$$CAR_{it} = \mu_i + \alpha_i UE_{it} + e_{it}, \ t=1, \ \ldots, \ T \tag{3.15}$$

For each time period τ, an estimate of the theoretical cross-sectional ERC, denoted $w\alpha_\tau$, is obtained by substituting the firm-specific ERC estimates (denoted $\hat{\alpha}_i$) into the right hand side of equation (3.3). The

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[18]In estimating firm-specific ERCs, observations with outliers in unexpected earnings are deleted. This is done to obtain a good proxy for the true firm-specific ERCs. The outlier detection procedure is conducted as follows. For each firm, 20 ERCs are estimated by deleting one observation at a time using a jackknife approach. If all or none of the 20 ERC estimates are statistically significant at the 0.10 level, then I consider these firms as having no outliers, since the statistical significance or otherwise of the price-earnings relation for these firms is not driven by any single observation. For 36.8% of the sample firms (i.e., 250 firms), all 20 ERC estimates are statistically significant, whereas for 19.9% of the sample firms (135 firms), none of the twenty estimates are significant. The firm-specific ERCs for these firms are estimated using all 20 observations.

I then isolate firms for which the statistical significance or otherwise of the price-earnings relation is driven by few observations. Of the remaining 294 firms, statistical significance/insignificance (at the 0.10 level) of the price-earnings relation for 254 firms is driven by less than four observations. The firm-specific ERCs for these firms are estimated after dropping the "outlier" observations. The ERCs of the 40 remaining firms are estimated using all 20 observations.

No inferences are affected when the estimates are obtained without deleting outliers.

cross-sectional association between the weighted ($w\alpha_\tau$) and observed ($\hat{\alpha}_\tau$) ERC estimates indicates the role of the weights in the estimate of the cross-sectional ERC. Note, however, $\hat{\alpha}_\tau$ is estimated by an OLS regression of $CAR_{i\tau}$ on $UE_{i\tau}$. Similarly, $w\alpha_\tau$ is a weighted average of firm-specific ERC estimates obtained by including the observation at time τ. Therefore, observed correlation between $w\alpha_\tau$ and $\hat{\alpha}_\tau$ could be spuriously driven by the inclusion of $CAR_{i\tau}$ and $UE_{i\tau}$ in estimating both $w\alpha_\tau$ and $\hat{\alpha}_\tau$.[19]

To control for this possibility, I obtain time-specific ERCs for each firm using a Jackknife approach. For the i-th firm at time τ, I estimate a firm-specific ERC, denoted $\hat{\alpha}_{i,-\tau}$, by excluding the observation at time τ.[20] I then substitute $\hat{\alpha}_{i,-\tau}$'s into the right hand side of (3.3) to obtain an estimate of the theoretical cross-sectional ERC, denoted $w\alpha_\tau(JK)$. Observed correlation between $w\alpha_\tau(JK)$ and $\hat{\alpha}_\tau$ would not be spuriously driven by my estimation procedures.

The results of firm-specific single and jackknife regressions are provided in Table 3.2 Panels A and B, respectively. The distribution of statistics reported in Panel A is very similar to those in Panel B. The median ERC (R^2) in Panel A is almost the same as the median value in Panel B, and the reported mean and median values of ERC estimates are similar those observed in prior research (see e.g., Kormendi and Lipe [1987]).

Panel A of Table 3.3 provides descriptive information on the weighted ERCs ($w\alpha_\tau$ and $w\alpha_\tau(JK)$), the observed ERC ($\hat{\alpha}_\tau$), and the deviation of the observed from the weighted ERC. While the distribution of $w\alpha_\tau$

[19]The concern about spurious correlation is mitigated since, for some firms, the observation at time τ is automatically excluded in estimating firm-specific ERCs if it happens to be an outlier.

[20]In addition to excluding the observation at time τ, I also exclude the "outlier" observations.

Table 3.2
DESCRIPTIVE INFORMATION ON FIRM-SPECIFIC REGRESSION OF CUMULATIVE ABNORMAL RETURNS ON UNEXPECTED EARNINGS[1]

Panel A: Firm-Specific Single Regressions (n=679)[2]

$$CAR_{it} = \hat{\mu}_i + \hat{\alpha}_i UE_{it} + e_{it}$$

			Quartiles		
Variable	Mean	Std. Dev.	Q1	Median	Q3
$\hat{\alpha}_i$	2.606	3.292	0.653	1.757	3.456
$t(\hat{\alpha}_i)$	1.836	1.596	0.788	1.593	2.668
R^2%	18.593	17.683	3.770	13.490	28.670
p-value	0.153	0.204	0.008	0.064	0.221

Panel B: Firm-Specific Jackknife Regressions (n=13,580)[3]

$$CAR_{it} = \hat{\mu}_{i,-\tau} + \hat{\alpha}_{i,-\tau} UE_{it} + e_{it}$$

			Quartiles		
Variable	Mean	Std. Dev.	Q1	Median	Q3
$\hat{\alpha}_{i,-\tau}$	2.620	3.359	0.661	1.763	3.472
$t(\hat{\alpha}_{i,-\tau})$	1.789	1.583	0.754	1.584	2.597
R^2%	18.813	17.906	3.923	13.650	28.900
p-value	0.157	0.207	0.010	0.066	0.231

[1]The p-values are one-tailed. 'n' refers to the number of regression estimates. The earnings response coefficients are estimated after deleting outliers. CAR refers to cumulative market-model abnormal returns from January to December and UE refers to change in income before extraordinary items and discontinued operations per share divided by prior year's stock price.

[2]A single earnings response coefficient is estimated for each firm.

[3]For each firm at time τ, a separate earnings response coefficient, denoted $\hat{\alpha}_{i,-\tau}$, is estimated by excluding the observation at time τ.

Table 3.3
ASSOCIATION BETWEEN THE CROSS-SECTIONAL AND WEIGHTED FIRM-SPECIFIC EARNINGS RESPONSE COEFFICIENTS[1]

$$CAR_{i\tau} = \hat{\mu}_\tau + \hat{\alpha}_\tau UE_{i\tau} + e_{i\tau}$$

Panel A: Descriptive Information[2]

Variable	Mean	Std. Dev.	Quartiles Q1	Median	Q3
$\hat{\alpha}_\tau$	0.985	0.656	0.610	0.769	1.046
$w\alpha_\tau$	0.870	0.247	0.724	0.782	0.902
DIFF %	5.036	36.300	-19.255	-4.877	28.442
$w\alpha_\tau$(JK)	1.011	0.345	0.777	0.928	1.126
DIFF(JK) %	-7.578	34.778	-33.344	-11.831	5.871

Panel B: Correlations[3]

$\rho(\hat{\alpha}_\tau, w\alpha_\tau)$ Pearson	$\rho(\hat{\alpha}_\tau, w\alpha_\tau)$ Spearman	$\rho(\hat{\alpha}_\tau, w\alpha_\tau(JK))$ Pearson	$\rho(\hat{\alpha}_\tau, w\alpha_\tau(JK))$ Spearman
0.962	0.883	0.800	0.726

[1]The analysis is based on 20 observations. CAR refers to cumulative market-model abnormal returns from January to December and UE refers to change in income before extraordinary items and discontinued operations per share divided by prior year's stock price. $w\alpha_\tau$ is the Weighted average of the firm-specific earnings response coefficients and $w\alpha_\tau$(JK) is the weighted average of the firm-specific Jackknife earnings response coefficients, with weights being the squared $UE_{i\tau}$.

[2]Both t-tests and signed-rank tests cannot reject the null hypothesis for the DIFF variables.

[3]All correlations are significant at the 0.01 level, one-tailed tests.

closely follows that of $\hat{\alpha}_\tau$, the distribution of $w\alpha_\tau$(JK) is shifted slightly to the right of $\hat{\alpha}_\tau$. However, the deviation of the observed ERC from either of the weighted ERCs is not significantly different from zero using both parametric and nonparametric tests (not reported).

Panel B provides the correlations between the weighted ERCs and the observed ERC. While both weighted ERCs are highly correlated with the observed ERC, the magnitude of the correlations is smaller when the weighted ERC is estimated using the jackknife approach. This is consistent with my prediction that correlation between $w\alpha_\tau$ and $\hat{\alpha}_\tau$ could be spuriously induced by the inclusion of the observation at τ in computing both variables. However, assuming no measurement error in unexpected earnings, it seems that a major portion of the intertemporal instability in the ERC can be attributed to the weighting scheme (see equation(3.3)). In fact, more than 60% of the variability in $\hat{\alpha}_\tau$ is explained by $w\alpha_\tau$(JK),[21] which is remarkable given that the covariance of $CAR_{i\tau}$ with current period earnings does not enter into the computation of $w\alpha_\tau$(JK). Overall, the empirical evidence is consistent with my prior arguments.

3.2.3 Measurement Error in Unexpected Earnings

In essence, this essay argues that the low magnitude of both the cross-sectional and firm-specific ERCs is primarily driven by measurement error in unexpected earnings. To examine the role of measurement error, assume (as in (3.4)) that earnings are measured with error. Now consider the firm-specific ERC estimate from regressing y_{it} on x^*_{it}:

$$\alpha^*_i = \hat{\sigma}(y_i, x^*_i)/\hat{\sigma}^2(x^*_i) \tag{3.16}$$

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[21]The Spearman correlation between $\hat{\alpha}_\tau$ and $w\alpha_\tau$ ($w\alpha_\tau$(JK)) decreases to 0.820 (0.690) when the firm-specific ERCs are estimated without deleting outliers.

Noting that $y_{it} = x_{it}\alpha_i + \epsilon_{it}$ (see (3.1)) and taking the probability limit, yields (see Schmidt [1976, p. 106]:

$$\text{plim}(\alpha^*_i) = \alpha_i\sigma^2(x_i)/[\sigma^2(x_i) + \sigma^2(\xi_i)] \tag{3.17}$$

The cross-sectional association between α^*_i and $\sigma^2(x^*_i)$ depends on the relative importance of measurement error versus true unexpected earnings in x^*_i. To see this, consider the partial derivative of (3.17) with respect to $\sigma^2(x_i)$ and $\sigma^2(\xi_i)$, i.e.,[22]

$$\partial\text{plim}(\alpha^*_i)/\partial\sigma^2(x_i) = \alpha_i\sigma^2(\xi_i)/[\sigma^2(x_i) + \sigma^2(\xi_i)]^2 \tag{3.18}$$

$$\partial\text{plim}(\alpha^*_i)/\partial\sigma^2(\xi_i) = -\alpha_i\sigma^2(x_i)/[\sigma^2(x_i) + \sigma^2(\xi_i)]^2 \tag{3.19}$$

The direction of the association between α^*_i and $\sigma^2(x^*_i)$ depends on the noise variance to the signal variance ratio. If $\sigma^2(x^*_i)$ is primarily driven by $\sigma^2(x_i)$, then one would expect a positive cross-sectional association between α^*_i and $\sigma^2(x^*_i)$.[23] On the contrary, if measurement error accounts for a significant portion of $\sigma^2(x^*_i)$, then one would observe a negative association between α^*_i and $\sigma^2(x^*_i)$.

The correlation between the firm-specific ERC estimate ($\hat{\alpha}_i$) and its components is provided in Panel A of Table 3.4 where $\hat{\sigma}_i$(CAR,UE) and $\hat{\sigma}^2_i$(UE) refer to the numerator and denominator of the firm-specific ERC estimate from model (3.15).[24] The strong positive correlation between $\hat{\sigma}_i$(CAR,UE) and $\hat{\sigma}^2_i$(UE) suggests that the "true signal" accounts for a significant portion of the variability in unexpected earnings. However, the

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[22]Note that $\sigma^2(x^*_i)$ is equal to the sum of $\sigma^2(x_i)$ and $\sigma^2(\xi_i)$.

[23]This is true only when there is measurement error in unexpected earnings. If $\sigma^2(\xi_i)$ equals zero, then the derivative with respect to $\sigma^2(x_i)$ will be zero also.

[24]As in Section 3.2.2, the firm-specific ERC estimate as well as its components are obtained after deleting 'outliers.' However, none of the inferences are affected when the estimates are obtained without deleting outliers.

Table 3.4
CROSS-SECTIONAL CORRELATION BETWEEN THE FIRM-SPECIFIC EARNINGS RESPONSE COEFFICIENT AND ITS COMPONENTS[1]

$$CAR_{it} = \hat{\mu}_i + \hat{\alpha}_i UE_{it} + e_{it}$$

Panel A: Sample Firms (n=679)[2]

$(\hat{\alpha}_i$ & $\hat{\sigma}_i(CAR.UE))$	$(\hat{\alpha}_i$ & $\hat{\sigma}^2_i(UE))$	$(\hat{\sigma}_i(CAR.UE)$ & $\hat{\sigma}^2_i(UE))$
−0.125c	−0.243c	0.712c
(0.081)b	(−0.476)b	(0.757)c

Panel B: Simulated Firms with Random Walk Persistence (n=1,000)[3,4]

k	$(\hat{\alpha}_i$ & $\hat{\sigma}_i(CAR.UE))$	$(\hat{\alpha}_i$ & $\hat{\sigma}^2_i(UE))$	$(\hat{\sigma}_i(CAR.UE)$ & $\hat{\sigma}^2_i(UE))$
0	0.022	0.014	1.000c
	(0.026)	(0.014)	(1.000)c
1	0.055a	−0.249c	0.933c
	(0.052)	(−0.224)c	(0.950)c
2	0.058a	−0.364c	0.864c
	(0.064)b	(−0.338)c	(0.895)c
5	0.072b	−0.456c	0.752c
	(0.096)c	(−0.466)c	(0.796)c
10	0.088c	−0.466c	0.673c
	(0.143)c	(−0.523)c	(0.718)c

Table 3.4 (Cont'd.).

Panel C: Simulated Firms with Varying Persistence (n=1,000)[3,5]

k	($\hat{\alpha}_i$ & $\hat{\rho}_i$(CAR,UE))	($\hat{\alpha}_i$ & $\hat{\sigma}^2_i$(UE))	($\hat{\rho}_i$(CAR,UE) & $\hat{\sigma}^2_i$(UE))
0	0.573c	0.010	0.741c
	(0.555)c	(0.013)	(0.787)c
1	0.521c	−0.099c	0.695c
	(0.528)c	(−0.075)b	(0.758)c
2	0.462c	−0.204c	0.648c
	(0.496)c	(−0.163)c	(0.726)c
5	0.367c	−0.327c	0.575c
	(0.455)c	(−0.288)c	(0.666)c
10	0.306c	−0.367c	0.527c
	(0.440)c	(−0.362)c	(0.616)c

[1]'n' refers to the number of observations. A 'c' (b/a) designates statistical significance at the 0.01 (0.05/0.10) level, two-tailed tests.

[2]CAR refers to the cumulative market-model abnormal returns from January to December, and UE is the change in income before extraordinary items and discontinued operations per share divided by prior year's stock price.

[3]The simulation is conducted assuming a linear relation between CAR and the "true" unexpected earnings. CAR is simulated assuming that the "true" unexpected earnings and the portion of CAR unrelated to earnings are independently and Normally distributed with mean zero and variances Uniformally distributed between zero and one. The measurement error in the "observed" unexpected earnings (i.e., UE) is also assumed independently and Normally distributed with mean zero and a variance such that the ratio of the variance of measurement error to the ratio of the "true" unexpected earnings is k_i. We assume that k_i is Uniformally distributed between zero and k.

[4]The earnings response coefficient is assumed to 11, which is the persistence of a random walk series assuming a discount rate of 10%.

[5]The earnings response coefficient is assumed to be Uniformally distributed between one and 11.

correlation of $\hat{\alpha}_i$ with its components ($\hat{\sigma}_i$(CAR,UE) and $\hat{\sigma}^2_i$(UE)) suggests that the magnitude of $\hat{\alpha}_i$ is primarily driven by its denominator, i.e., $\hat{\sigma}^2_i$(UE). The magnitude of the Spearman correlations of $\hat{\alpha}_i$ with $\hat{\sigma}_i$(CAR,UE) and $\hat{\sigma}^2_i$(UE) suggests that the dominant effect on $\hat{\alpha}_i$ is from the variance $\hat{\sigma}^2_i$(UE) and not from the covariance $\hat{\sigma}_i$(CAR,UE). The strong negative association between $\hat{\alpha}_i$ and $\hat{\sigma}^2_i$(UE) suggests, per equation (3.19), that measurement error in unexpected earnings significantly downward biases the ERC estimate.

While the true ERC and the variance of true unexpected earnings should be uncorrelated, one could argue that, by construction, their empirical counterparts are negatively correlated. For example, the negative correlation between $\hat{\alpha}_i$ and $\hat{\sigma}^2_i$(UE) could be spuriously driven by the fact that $\hat{\sigma}^2_i$(UE) enters in the denominator when estimating $\hat{\alpha}_i$. To address this issue, I conduct a simulation analysis to empirically document the role of measurement error.

First, assume that model (3.1) is the true return generating process and that both x_{it} and ϵ_{it} are independently and Normally distributed with mean zero and variances $\sigma^2(x_i)$ and $\sigma^2(\epsilon_i)$ respectively, where $\sigma^2(x_i)$ and $\sigma^2(\epsilon_i)$ are Uniformally distributed between zero and one. With respect to the ERC, consider two independent scenarios. In the first scenario, assume a constant α_i of 11 across all firms. (Note the persistence of a random walk series assuming a discount rate of 10% is 11.). In the second scenario, assume that α_i is Uniformally distributed between one and 11. (The lower bound of one is chosen since it represents the persistence of a purely transitory or White noise process.).

Second, I generate unexpected earnings according to model (3.4) where ξ_{it} is independently and Normally distributed with mean zero and variance $\sigma^2(\xi_i)$. To see the effect of varying the level of measurement error, assume that the ratio of $\sigma^2(\xi_i)$ to $\sigma^2(x_i)$ (denoted k_i) is Uniformally distributed between zero and k, where k captures the magnitude of the noise to signal ratio. For example, when k is equal to one, on average, the variability of measurement error is equal to one-half of the variability of "true" unexpected earnings. Note that model (3.1) results when k is equal to zero. Varying k, I document the effect of the level of measurement error on the association between the ERC and its components.

I simulate the stock returns and unexpected earnings for 1000 firms with 100 observations per firm. Unexpected earnings is computed for five different levels of k, i.e., k = 0, 1, 2, 5, and 10. Stock returns are generated under both the constant and varying persistence assumptions. Based on the simulated series, I estimate the ERC and its components for each "firm."

For the constant persistence scenario, the cross-sectional correlations among the estimates are provided in Panel B of Table 3.4. For k=0, while $\hat{\sigma}_i$(CAR,UE) and $\hat{\sigma}^2{}_i$(UE) are perfectly correlated, there is no significant association between $\hat{\alpha}_i$ and its components. Especially, the lack of a significant association between $\hat{\alpha}_i$ and $\hat{\sigma}^2{}_i$(UE) is consistent with expectations. However, as k is increased, the association between $\hat{\alpha}_i$ and $\hat{\sigma}^2{}_i$(UE) becomes more negative, which reflects the fact that measurement error accounts for an increased proportion of the variance of unexpected earnings.

Additionally, the measurement error induces a spurious positive association between $\hat{\alpha}_i$ and $\hat{\sigma}_i$(CAR,UE). While the strength of this association increases with k, the magnitude of the correlation is relatively small. In addition, as the noise to signal ratio increases, the correlation between $\hat{\sigma}_i(CAR,UE)$ and $\hat{\sigma}^2_i(UE)$ decreases. Overall, the simulation results in Panel B suggest that the observed association among $\hat{\alpha}_i$ and its components is consistent with the measurement error argument. For example, the Spearman correlations reported in Panel B for k=5 are very similar to those reported in Panel A for the sample firms. While I do not claim that the earnings process assumed in the simulation is a good proxy for the "true" earnings process, the observed association between $\hat{\alpha}_i$ and its components for the sample firms is consistent with large measurement in unexpected earnings.

In varying persistence scenario, cross-sectional correlations among the ERC estimate and its components are provided in Panel C of Table 3.4. While the magnitude is smaller than in Panel B, the correlation between $\hat{\alpha}_i$ and $\hat{\sigma}^2_i(UE)$ becomes increasingly negative with k. However, the assumption of varying persistence significantly affects the association of $\hat{\alpha}_i$ and $\hat{\sigma}^2_i(UE)$ with $\hat{\sigma}_i(CAR,UE)$. Even without measurement error, there is no one-to-one correspondence between $\hat{\sigma}_i(CAR,UE)$ and $\hat{\sigma}^2_i(UE)$ under the varying persistence scenario. For K=0, compared to the perfect Spearman correlation between $\hat{\sigma}_i(CAR,UE)$ and $\hat{\sigma}^2_i(UE)$ in Panel B, the correlation is only 0.787 in Panel C. Similarly, for all chosen levels of k, the reported correlation between $\hat{\sigma}_i(CAR,UE)$ and $\hat{\sigma}^2_i(UE)$ is lower in Panel C compared to Panel B.

Unlike Panel B, there is a strong positive association between $\hat{\alpha}_i$ and $\hat{\sigma}_i(CAR,UE)$ in Panel C. Since I assume varying persistence, a portion of the cross-sectional variability in $\hat{\sigma}_i(CAR,UE)$ is attributable to the cross-sectional differences in α_i. However, as K increases, the magnitude of the association between $\hat{\alpha}_i$ and $\hat{\sigma}_i(CAR,UE)$ decreases. While increasing measurement error induces a positive association between $\hat{\alpha}_i$ and $\hat{\sigma}_i(CAR,UE)$

in Panel B, it dampens the positive association in Panel C. Thus, the assumption of varying versus constant persistence significantly affects the expected association of $\hat{\alpha}_i$ and $\hat{\sigma}^2{}_i(UE)$ with $\hat{\sigma}_i(CAR,UE)$.

Although reported correlations in Panel A resemble those in Panel B, one cannot conclude that the constant persistence scenario is a better proxy for the "true" price-earnings relation based on the limited simulation results. However, the simulation indicates that the observed negative correlation between $\hat{\alpha}_i$ and $\hat{\sigma}^2{}_i(UE)$ is consistent with the measurement error argument both under the constant and varying persistence scenarios.

Given the importance of measurement error, it would be valuable to identify the sources of such measurement error. I investigate a potential source of measurement error apparent from the results in Table 3.1—the temporal decline in the cross-sectional ERC estimate. Similar to the firm-specific scenario, I estimate the correlations among the cross-sectional ERC estimate ($\hat{\alpha}_\tau$) and its components ($\hat{\sigma}_\tau(CAR,UE)$ and $\hat{\sigma}^2{}_\tau(UE)$). The correlation estimates are provided in Panel A of Table 3.5. In addition, I provide the correlation of the ERC estimates and its components with year.

The cross-sectional results in Table 3.5 are similar to those observed in Table 3.4 for the firm-specific case. The magnitude of the cross-sectional ERC is primarily driven by $\hat{\sigma}^2{}_\tau(UE)$. In addition, while both $\hat{\sigma}_\tau(CAR,UE)$ and $\hat{\sigma}^2{}_\tau(UE)$ are significantly positively associated with year, the ratio of the two (i.e., $\hat{\alpha}_\tau$) has a strong negative association with year. This suggests that the denominator effect dominates the numerator effect in determining the magnitude of the cross-sectional ERC.

Table 3.5
ASSOCIATION BETWEEN THE CROSS-SECTIONAL EARNINGS RESPONSE COEFFICIENT AND ITS COMPONENTS[1]

$$CAR_{i\tau} = \hat{\mu}_\tau + \hat{\alpha}_\tau UE_{i\tau} + e_{i\tau}$$

Panel A: Correlation Results[2]

	$\hat{\alpha}_\tau$	$\hat{\sigma}_\tau$(CAR,UE)	$\hat{\sigma}^2_\tau$(UE)
Year	−0.695c (−0.708)c	0.477b (0.519)b	0.775c (0.782)c
$\hat{\alpha}_\tau$		−0.262 (−0.068)	−0.584c (−0.520)b
$\hat{\sigma}_\tau$(CAR,UE)			0.810c (0.838)c

Panel B: Descriptive Information

Year	$\hat{\alpha}_\tau$	$\hat{\sigma}_\tau$(CAR,UE)	$\hat{\sigma}^2_\tau$(UE)	$\hat{\sigma}^2_\tau$(CAR)
68	2.7777	0.0093	0.0033	0.1781
69	2.5022	0.0019	0.0008	0.0698
70	1.7451	0.0038	0.0022	0.0672
71	1.0937	0.0068	0.0062	0.1129
72	0.5693	0.0022	0.0039	0.0912
73	0.8147	0.0043	0.0053	0.0757
74	0.7394	0.0160	0.0217	0.0634
75	0.7815	0.0301	0.0385	0.1521
76	0.9018	0.0263	0.0292	0.1188
77	0.6772	0.0090	0.0134	0.0682
78	0.7558	0.0103	0.0136	0.0915
79	1.4624	0.0256	0.0175	0.2205
80	0.8119	0.0141	0.0174	0.1241
81	0.7046	0.0123	0.0175	0.0929
82	0.8407	0.0258	0.0307	0.1554
83	0.7303	0.0182	0.0250	0.1141
84	0.3162	0.0064	0.0201	0.0616
85	0.3843	0.0140	0.0365	0.0985
86	0.5881	0.0188	0.0320	0.1033
87	0.5031	0.0218	0.0434	0.1020

[1]CAR refers to cumulative market-model abnormal returns from January to December and UE refers to change in income before extraordinary items and discontinued operations per share divided by prior year's stock price.

[2]The numbers are Pearson (Spearman) correlations. A 'c' (b) designates statistical significance at the 0.01 (0.05) level, two-tailed tests.

This monotonic decline in the annual ERC estimate is also reported by Rayburn [1986]—see Table 3.1.

The cross-sectional ERC estimate ($\hat{\alpha}_\tau$) and its components ($\hat{\sigma}_\tau$(CAR,UE) and $\hat{\sigma}^2_\tau$(UE)) are provided in Panel B. In addition, the cross-sectional variance estimate of CAR (denoted $\hat{\sigma}^2_\tau$(CAR)) is provided. Panel B indicates while $\hat{\sigma}_\tau$(CAR,UE) has more than doubled from 1968 to 1987, $\hat{\sigma}^2_\tau$(UE) has increased more than ten fold during the same period, explaining the 80% decrease in the ERC estimate from 1968 to 1987. Although the cross-sectional variability of unexpected earnings has increased over time, there is no such trend in the variability of CAR. Overall, the evidence is consistent with significant time-dependent measurement error in unexpected earnings.

In summary, the observed negative association between $\hat{\alpha}_i$ and $\hat{\sigma}^2_i$(UE) suggests that measurement error in unexpected earnings is a major reason for the observed low magnitude of ERCs. Identifying the sources of such firm-specific measurement error would be valuable. I provide empirical evidence suggesting that a potential source of measurement error—the temporal decline of ERC—is the temporally increasing <u>firm-specific</u> variance of unexpected earnings.

3.2.4 <u>Diversification of Measurement Error</u>

The evidence in Section 3.2.3 indicates that measurement error in unexpected earnings not only downward biases the ERC estimates, but also causes significant temporal instability in the cross-sectional ERCs. Since the evidence is consistent with a temporally increasing noise-to-signal ratio, increased <u>stability</u> in the ERC estimates can be achieved by controlling for time-dependent measurement error. To illustrate this, I randomly assign each firm-year to one of 20 groups (hereafter, random groups), and estimate the regression model (3.13) for each of the 20 groups. Though this approach does not minimize the overall noise-to-signal ratio, it minimizes the differences in the noise-to-signal ratio across subsamples. While this increases the stability of the cross-sectional ERC estimates, it does not rectify the downward bias induced by the measurement error problem.

The regression results for the random groups are provided in Panel A of Table 3.6. The parameter estimates are denoted $\hat{\mu}_{RG}$ and $\hat{\alpha}_{RG}$. While the median values of the ERC estimate, t-statistic, and R^2 are similar between Tables 3.1 and 3.6, there is significant improvement in the cross-sectional stability of the ERC estimate in the random group regressions versus the annual regressions. While the ERC estimates in Table 3.6 range from 0.316 to 2.778, those in Table 3.5 range from 0.523 to 1.173. In addition, the Chow tests of all pairs of random group ERCs (see Panel B) reject the null hypothesis of intergroup stability only 13.68% of the time at the 0.01 level compared to 48.42% for the annual ERCs. However, as already argued, the magnitude of the ERC estimates is still smaller since the random group approach does not eliminate the measurement error problem.

Panel C of Table 3.6 provides the correlations between the weighted ERCs and the observed ERCs for the random groups. The weighted ERCs of the random groups computed using firm-specific single (jackknife) ERC estimates is denoted $w\alpha_{RG}$ ($w\alpha_{RG}$(JK)). While $\hat{\alpha}_{RG}$ is significantly correlated with $w\alpha_{RG}$, there is no statistically significant association between $\hat{\alpha}_{RG}$ and $w\alpha_{RG}$(JK). The correlation between $\hat{\alpha}_{RG}$ and $w\alpha_{RG}$ is spuriously driven by the estimation procedure used to obtain firm-specific single ERC estimates.

Table 3.6
REGRESSION OF CUMULATIVE ABNORMAL RETURNS ON UNEXPECTED EARNINGS BY RANDOM GROUPS[1]

Panel A: Regression Results[2]

$$CAR_{it} = \hat{\mu}_{RG} + \hat{\alpha}_{RG}UE_{it} + e_{it}$$

Group	$\hat{\mu}_{RG}$	$\hat{\alpha}_{RG}$	$t(\hat{\alpha}_{RG})$	R^2
1	0.0051	0.7464	8.371	9.38
2	−0.0031	0.6945	7.713	8.08
3	0.0089	0.6976	7.136	7.00
4	−0.0056	0.5651	7.882	8.40
5	0.0010	0.7055	7.344	7.38
6	−0.0274	1.0057	9.664	12.12
7	−0.0200	0.6031	6.488	5.85
8	0.0052	1.1730	12.520	18.80
9	0.0000	0.5229	5.792	4.72
10	−0.0270	0.5291	6.429	5.75
11	−0.0243	0.7333	9.093	10.88
12	−0.0114	0.8806	10.321	13.60
13	0.0078	0.8027	8.936	10.55
14	−0.0161	0.8499	9.434	11.62
15	−0.0107	0.5574	5.741	4.64
16	−0.0128	0.6900	8.900	10.47
17	−0.0131	0.8075	7.878	8.40
18	−0.0128	0.6436	7.890	8.42
19	−0.0006	0.7872	9.271	11.26
20	−0.0094	0.7876	8.440	9.52
Median		0.7194	8.131	8.90

Panel B: Chow Tests for Differences of Coefficients

Rejection of null at chosen alpha levels				
10%	5%	1%	Median F	Median P
32.63%	24.74%	13.68%	1.336	0.2477

Panel C: Association between Random Group ERCs and weighted ERCs[3]

$\rho(\hat{\alpha}_{RG}, w\alpha_{RG})$		$\rho(\hat{\alpha}_{RG}, w\alpha_{RG}(JK))$	
Pearson	Spearman	Pearson	Spearman
0.339a	0.313a	0.077	0.179

Table 3.6 (Cont'd.).

[1]Firm-years (13,580) are randomly sorted, and divided into 20 groups with equal number of observations (679) in each. For each group, the earnings response coefficient is estimated by regressing CAR on UE using all observations. CAR refers to cumulative market-model abnormal returns from January to December and UE refers to change in income before extraordinary items and discontinued operations per share divided by prior year's stock price. $w\alpha_{RG}$ is the weighted average of the firm-specific earnings response coefficients and $w\alpha_{RG}(JK)$ is the weighted average of the firm-specific Jackknife earnings response coefficients, with weights being the squared $UE_{i,RG}$.

[2]All t-statistics are significant at the 0.01 level, one-tailed tests.

[3]A 'a' designates significance at the 0.10 alpha level, one-tailed tests.

The observed association between the weighted and the cross-sectional ERCs (see Panel B of Table 3.3) disappears after diversifying the measurement error using random groups, suggesting that the association between the weighted and the annual ERCs is driven by the temporal differences in measurement error. To formally examine this, consider the probability limit of the weighted ERC where unexpected earnings is measured with error:

$$\text{plim}(w\alpha) = \frac{[\sum_i (x^2_{i\tau} + \xi^2_{i\tau})\text{plim}(\alpha_i^*)]/\sum_i x^2_{i\tau}}{1 + (\sigma^2(\xi_\tau)/\sigma^2(x_\tau))} \tag{3.20}$$

where $\text{plim}(\alpha_i^*)$ is as per (3.17).

The downward bias in $\text{plim}(\alpha_i^*)$ is compensated by its disproportionately larger weights (i.e., $x^2_{i\tau} + \xi^2_{i\tau}$ in (3.20) versus $x^2_{i\tau}$ in (3.3)). Thus, the numerator in (3.20) should be approximately equal to $\text{plim}(\alpha^*_\tau)$, the numerator in (3.6). Given this, the weighting scheme adopted in estimating $w\alpha$ should provide consistent estimates of the cross-sectional ERC whether or not unexpected earnings are measured with error.

Although I expect a constant noise-to-signal ratio across the random groups, I observe monotonically increasing measurement error in the annual groups. Thus, while the variability in the annual ERCs is driven both by the weighting scheme as well as the noise-to-signal ratio, that of the random ERCs is driven by the weighting scheme alone. If the weighting scheme (i.e., the "inherent variability") is the primary source of the ERC variability, then I should observe high association between the weighted and observed ERCs for both the annual and random cases. The lack of association in the random case suggests that intertemporal differences in the noise-to-signal ratio (denominator of equation (3.6)) lead to significant intertemporal instability in the ERC estimates.

3.2.5 Tests for Temporally Increasing Measurement Error

The evidence in Section 3.2.3 is consistent with a temporally increasing firm-specific noise-to-signal ratio. However, it is not necessary for all sample firms' earnings to exhibit such behavior to produce temporally declining cross-sectional ERC. Clearly, the larger the number of firms with temporally increasing measurement error, the greater the rate of decline in the cross-sectional ERC. Alternatively, a small number of firms with temporally declining measurement error could be swamped by a large number of firms with temporally increasing measurement error to produce the observed result. Also, it is not necessary for all affected firms to exhibit increased measurement from the beginning of the sample period. If different subsets of firms start to exhibit the variance shift behavior at different points in the sample period, then I would still observe a temporally declining cross-sectional ERC. Establishing this type of a linkage to firm-specific noise-to-signal ratio is crucial if one has to ultimately identify firm-specific determinants of measurement error.

Based on the analysis in Section 3.2.3, I posit that increase in the variance of unexpected earnings is, on average, the result of increased measurement error, and try to identify firms with increasing variance of unexpected earnings over time. Specifically, I divide the sample period (1968-87) into four equal subperiods, and compute the firm-specific variance of unexpected earnings for each subperiod (denoted $\hat{\sigma}^2_{is}(UE)$). I compute an F-statistic using the ratio of adjacent variances, and conduct a test for significant variance increase (at an alpha level of 0.10) from one period to the next. Given four subperiods, I conduct three variance shift tests. Based on the results of the tests, I assign the sample firms into one of four groups such that firms in Group 1 and Group 4 have respectively zero and three adjacent variance increases in unexpected earnings. Firms with one and two variance increases are assigned to Groups 2 and 3 respectively.

I compute a firm-specific ERC for each subperiod, denoted α_{is}. Using these ERCs, I compute a weighted average subperiod ERC for each variance increase group, with weights being the inverse of the standard error of the ERC estimates (see Lys and Sohn [1991]). The statistical significance of the weighted ERC is tested using Christie's Z-statistic (Christie [1990]). The weighted ERCs together with the results of the Z-tests are provided in Panel A of Table 3.7.

It is evident from Panel A that almost 85% of the sample firms have had at least one variance increase during the sample period. However, the majority of the firms exhibit only one variance increase during the sample period. While 15% of the firms have constant variance across the sample period, 2.5% of the firms exhibit a continuous variance increase across the four subperiods.

The inter-temporal behavior of the weighted ERCs is consistent with the measurement error argument. The evidence also sheds light on inter-firm differences in measurement error behavior. While there is no decrease in the weighted ERC of Group 1, the weighted ERCs of the other three groups show a declining trend.[25] In addition, while the Group 2 ERC declines only from the first to the second subperiod, the ERCs of

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[25]The weighted ERCs of Group 1 are higher in the second half of the sample period compared to the first half. This evidence is consistent with temporally declining measurement error for Group 1 firms—see Panel B of Table 3.7.

Table 3.7
WEIGHTED AVERAGE FIRM-SPECIFIC SUB-PERIOD EARNINGS RESPONSE COEFFICIENTS BY VARIANCE CHANGE GROUPS[1]

$$CAR_{it} = \hat{\mu}_{is} + \hat{\alpha}_{is}UE_{it} + e_{it}$$

Panel A: Variance Increase Groups[2]

	Weighted Average $\hat{\alpha}_{is}$			
Sub-Period	Group 1 (n=105)	Group 2 (n=392)	Group 3 (n=165)	Group 4 (n=17)
68-72	1.6313	4.5335	4.2521	5.0453
73-77	1.7143	1.4555	1.6466	2.0141&
78-82	2.9319	1.4703	1.3990	2.2927
83-87	2.3173	1.6379	0.7142	0.4939

Panel B: Variance Decrease Groups[3]

	Weighted Average $\hat{\alpha}_{is}$		
Sub-Period	Group 1 (n=412)	Group 2 (n=242)	Group 3 (n=25)
68-72	4.1510	3.0123	1.7665
73-77	1.9170	1.3063	0.8629
78-82	1.5571	1.6889	2.3328
83-87	0.9783	1.6704	6.1180

[1]The sample period (1968-87) is subdivided into four equal subperiods. For each firm, four subperiod earnings response coefficients (ERC) are computed. A weighted average of the subperiod ERCs is computed for each group with weights being the inverse of the ERC's standard error. The significance of the weighted average ERCs are tested using Christie's aggregation Z-statistic. 'n' refers to the number of firms. An '&' indicates that the coefficient is not significant at the 0.05 level, one-tailed tests.

[2]For each firm, three F-statistics are constructed to test for significant variance increases (at an alpha of 0.10) from one subperiod to the next. Firms with zero to three variance increases are assigned to Group 1 to Group 4 respectively.

[3]For each firm, three F-statistics are constructed to test for significant variance decreases (at an alpha of 0.10) from one subperiod to the next. Firms with zero to two variance decreases are assigned to Group 1 to Group 3 respectively. No firm exhibited three variance decreases during the sample period.

Groups 3 and 4 show a declining trend over the whole sample period. Thus, a relatively small subset of firms in Groups 3 and 4 (182 firms) significantly contributes to the observed inter-temporal decline in the cross-sectional ERCs—see Table 3.5.

3.2.6 <u>Tests for Temporally Decreasing Measurement Error</u>

If increase in the variance of the unexpected earnings signals increased measurement error, then a decrease in the variance should proxy for a lower noise-to-signal ratio. As in the variance increase test, I divide the sample period (1968-87) into four equal subperiods, and conduct a test for significant variance decrease (at an alpha level of 0.10) from one period to the next. Based on the test results, I assign the sample firms into one of three groups such that firms in Group 1 (Group 2/Group 3) have no (one/two) variance decrease in unexpected earnings.[26] The weighted ERCs of the variance decrease groups, together with the results of the Z-tests, are provided in Panel B of Table 3.7.

It is evident from Panel B that almost 61% of the sample firms have had no variance decline compared to only 3.7% of the sample firms with two variance declines during the sample period. The remaining firms exhibit only one variance decline. Compared to the number of variance increases, sample firms have had fewer variance declines. Therefore, except for Group 3, the other groups exhibit a temporally decreasing ERC indicating the disproportionate number of firms with variance increases. However, the dramatic increase in the ERC of Group 3 suggests that temporally declining $\hat{\sigma}^2_{is}(UE)$ is consistent with temporally declining measurement error.

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[26]None of the sample firms have three consecutive downward shifts in the variance of the unexpected earnings.

3.2.7 <u>Control for the Level of Measurement Error</u>

Ideally, I need to eliminate measurement error in unexpected earnings to obtain a consistent estimate of the cross-sectional ERC. Given that there is no simple way of accomplishing this, I estimate the relative levels of inconsistency in the ERC estimate across different levels of measurement error. This would indicate the closeness of the observed ERC estimates to the true ERC. For example, if the full sample ERC estimate is closer in magnitude to the ERC estimate of firms with a higher (lower) level of measurement error, then it is apparent that the higher (lower) measurement error in a subset of firms has a significant impact on the full sample ERC estimate.

While the analysis conducted so far controls for changes in measurement error over time, it does not control for the actual level of measurement error. For example, while firms in Group 1 (see Panel A of Table 3.7) exhibit relatively more intertemporal stability in the ERCs compared to firms in Group 4, the latter firms have higher magnitude of ERCs during the first half of the sample period. This is consistent with lower level of measurement error for the firms in Group 4 versus Group 1 in the first half of the sample period.

To provide additional evidence, I estimate the cross-sectional variance of unexpected earnings for each year for each of the variance shift groups. These variance estimates are reported in Table 3.8. While the estimates for the variance increase groups are provided in columns two through five, those for the variance decrease groups are provided in columns six through eight.

For the variance increase analysis, while firms in Group 1 exhibit relatively more intertemporal stability in $\hat{\sigma}^2_\tau$(UE) compared to the firms

Table 3.8
CROSS-SECTIONAL VARIANCE OF UNEXPECTED EARNINGS
BY VARIANCE CHANGE GROUPS[1]

	$\hat{\sigma}^2_T$(UE)						
	Variance Increase Groups				Variance Decrease Groups		
Year	Group 1 (n=105)	Group 2 (n=392)	Group 3 (n=165)	Group 4 (n=17)	Group 1 (n=412)	Group 2 (n=242)	Group 3 (n=25)
68	0.0153	0.0014	0.0006	0.0001	0.0025	0.0023	0.0285
69	0.0020	0.0006	0.0005	0.0000	0.0003	0.0011	0.0047
70	0.0064	0.0017	0.0007	0.0001	0.0012	0.0029	0.0114
71	0.0275	0.0025	0.0021	0.0002	0.0029	0.0078	0.0475
72	0.0157	0.0023	0.0005	0.0000	0.0007	0.0073	0.0259
73	0.0132	0.0045	0.0023	0.0002	0.0020	0.0035	0.0748
74	0.0130	0.0235	0.0243	0.0006	0.0108	0.0325	0.0914
75	0.0302	0.0484	0.0239	0.0016	0.0142	0.0612	0.2021
76	0.0120	0.0410	0.0146	0.0022	0.0081	0.0536	0.1309
77	0.0090	0.0173	0.0078	0.0032	0.0050	0.0234	0.0519
78	0.0142	0.0152	0.0102	0.0067	0.0094	0.0216	0.0065
79	0.0070	0.0214	0.0165	0.0021	0.0114	0.0288	0.0081
80	0.0034	0.0175	0.0273	0.0042	0.0084	0.0331	0.0121
81	0.0036	0.0186	0.0251	0.0035	0.0139	0.0238	0.0093
82	0.0090	0.0305	0.0453	0.0135	0.0352	0.0222	0.0134
83	0.0034	0.0179	0.0495	0.0850	0.0351	0.0095	0.0022
84	0.0012	0.0132	0.0368	0.1444	0.0283	0.0082	0.0016
85	0.0045	0.0184	0.0862	0.1714	0.0488	0.0190	0.0013
86	0.0112	0.0114	0.0760	0.2255	0.0420	0.0180	0.0020
87	0.0144	0.0118	0.1068	0.3574	0.0554	0.0274	0.0014

[1]The sample period (1968-87) is subdivided into four equal subperiods. For each firm, three F-statistics are constructed to test for significant variance increases (decreases) from one subperiod to the next at an alpha level 0.10. Firms with zero to three (two) variance increases (decreases) are assigned to Group 1 to Group 4 (Group 3) respectively. No firm exhibited three variance decreases during the sample period. For each group, cross-sectional variance of UE is computed for each year. 'n' refers to the number of firms. UE is the change in income before extraordinary items and discontinued operations per share divided by prior year's stock price.

in Group 4, the latter firms have lower levels of $\hat{\sigma}^2_T(UE)$ up until the late 70's. Firms in Groups 3 and 4 seem to have a lower level of measurement error in the first half of the sample period. Inspection of the variance decrease groups leads to similar conclusions. Although firms in Group 3 exhibit a significant decrease in $\hat{\sigma}^2_T(UE)$ over the sample period compared to the firms in Group 1, the latter firms have lower levels of $\hat{\sigma}^2_T(UE)$ during the first half of the sample period.

The grouping procedure adopted so far is inadequate to control for differences in the level of measurement error at the firm-specific level. On the other hand, the adopted procedure highlights the effects of changes in the level of measurement error on both the inter-temporal stability and the magnitude of the response coefficient.

In the spirit of the prior analysis, I use firm-specific subperiod variance (i.e., $\hat{\sigma}^2_{is}(UE)$) as a proxy for the level of measurement error in unexpected earnings. This is a more powerful proxy than a simple firm-specific variance estimate, since the evidence so far is consistent with significant temporal changes in the firm-specific variance. Given that each firm has four subperiod variance estimates, in total I have 2,716 variance estimates. I rank all 2,716 firm-subperiods on the level of the variance estimate, and assign them to one of four groups based on their relative rank. (Note all five observations in each subperiod are assigned to one group.). Firm-years in Group 1 have the lowest $\hat{\sigma}^2_{is}(UE)$ and those in Group 4 have the highest $\hat{\sigma}^2_{is}(UE)$.

Utilizing this grouping procedure, I estimate the following cross-sectional regression model both across all firm-years and separately for each year:

$$CAR_{i\tau} = \sum_{g=1}^{4}[\mu_{\tau g}D_g] + \sum_{g=1}^{4}[\alpha_{\tau g}D_g UE_{i\tau}] + e_{i\tau} \qquad (3.21)$$

where D_g takes value one if the firm-year belongs to Group g and zero otherwise, and $\alpha_{\tau g}$ is the cross-sectional ERC of Group g. The parameter estimates are denoted $\hat{\mu}_{\tau g}$ and $\hat{\alpha}_{\tau g}$.

The results of the pooled regression are provided in Panel A of Table 3.9. The results indicate that $\hat{\sigma}^2$(UE) is a major determinant of the magnitude of the earnings response coefficient. ERC estimates of six and 4.5 are achieved for the two low variance groups compared to 0.738 for the entire sample (see Table 3.1). Thus, controlling for the level of measurement error dramatically increases the ERC estimate.

The results also indicate that the larger the noise/signal ratio, the smaller is the earnings response coefficient. While the ERC estimate of Group 4 (0.637) is less than one-ninth of Group 1 (5.946), it is almost identical to that of the entire sample. Thus, even though the firm-years are equal across groups, the measurement error in Group 4 dominates the full sample ERC estimate.

Results in Table 3.4 indicate that not all cross-sectional differences in the variance of unexpected earnings are attributable to measurement error. A portion of the cross-sectional variability in $\hat{\sigma}^2$(UE) is due to the differences in the magnitude of the true signal across the variance level groups. To estimate the differential measurement error across groups, I compare the inter-group percentage changes in R^2 and σ^2(CAR) to that of σ^2(UE). In Panel B of Table 3.9, I provide the estimates of R^2, σ^2(CAR), and σ^2(UE) at each variance level (columns (2), (4), and (6)). In addition, the percentage changes in the three variables

Table 3.9
REGRESSION OF CUMULATIVE ABNORMAL RETURNS ON UNEXPECTED EARNINGS WITH INTERCEPT AND SLOPE DUMMIES FOR VARIANCE LEVELS[1]

$$CAR_{i\tau} = \sum_{g=1}^{4}(\hat{\mu}_{\tau g}D_g) + \sum_{g=1}^{4}(\hat{\alpha}_{\tau g}D_g UE_{i\tau}) + e_{i\tau}$$

Panel A: Regression Results for Pooled Sample (n=13,580)[2]

$\hat{\alpha}_{\tau 1}$	$\hat{\alpha}_{\tau 2}$	$\hat{\alpha}_{\tau 3}$	$\hat{\alpha}_{\tau 4}$	R^2
5.9458 (10.713)	4.4599 (18.890)	2.7373 (25.802)	0.6373 (32.266)	13.86

Panel B: Descriptive information on Separate Regression by Unexpected Earnings Variance Level[3]

Variance Level Group	R^2	$\%\Delta R^2$	$\hat{\sigma}^2_\tau$(CAR)	$\%\Delta\hat{\sigma}^2_\tau$(CAR)	$\hat{\sigma}^2_\tau$(UE)	$\%\Delta\hat{\sigma}^2_\tau$(UE)	$E[\%\Delta\hat{\sigma}^2_\tau(UE)]$
1) Low	5.91		0.05578		0.00009		
2)	13.95	135.96	0.07349	31.75	0.00052	452.54	167.71
3)	17.11	22.61	0.11184	52.18	0.00255	395.30	74.79
4) High	14.14	−17.34	0.21158	89.19	0.07367	2784.83	71.85

Panel C: Annual Regression Results (n=679)[4]

Year	$\hat{\alpha}_{\tau 1}$	$\hat{\alpha}_{\tau 2}$	$\hat{\alpha}_{\tau 3}$	$\hat{\alpha}_{\tau 4}$	R^2
68	15.643	12.342	5.618	2.140	32.58
69	11.303	10.502	2.970	0.963	33.09
70	6.516	3.991	2.718	0.562	24.38
71	11.705	6.519	4.322	0.638	21.31
72	6.290	6.442	3.760	0.376	19.96
73	7.398	2.777	5.175	0.764	16.51
74	7.938	2.762	1.541	0.658	30.09
75	6.884	4.071	2.748	0.684	24.27
76	4.580	3.664	3.072	0.757	34.34
77	10.387	3.160	2.688	0.544	26.40
78	2.751&	4.776	2.571	0.602	13.63
79	5.198&	5.121	3.128	1.281	21.62
80	7.733	4.382	3.340	0.672	25.43
81	8.262	4.059	2.675	0.592	20.66

Table 3.9 (Cont'd.).

Panel C (Cont'd.).

Year	$\hat{\alpha}_{\tau 1}$	$\hat{\alpha}_{\tau 2}$	$\hat{\alpha}_{\tau 3}$	$\hat{\alpha}_{\tau 4}$	R^2
82	4.422&	4.437	2.753	0.786	19.13
83	3.751&	3.348	2.415	0.648	18.50
84	4.486	2.034	1.827	0.304	23.06
85	7.601	7.029	1.846	0.309	19.79
86	5.572	2.779	2.128	0.561	20.68
87	4.855	3.245	2.098	0.454	16.94

Panel D: Year-Wise Frequency Distribution of Firms by UE Variance Levels

	Variance Level			
Years	Low	Low/Medium	Medium/High	High
1968-72	339	187	108	45
1973-77	145	162	177	195
1978-82	84	175	223	197
1983-87	111	155	171	242

Panel E: Pooled Subsample Regression Results (n=2716)[5]

Years	$\hat{\alpha}_{\tau 1}$	$\hat{\alpha}_{\tau 2}$	$\hat{\alpha}_{\tau 3}$	$\hat{\alpha}_{\tau 4}$	R^2
68, 73, 78, and 83	3.489	4.857	3.173	0.743	12.01
69, 74, 79, and 84	5.933	4.445	2.476	0.756	14.00
70, 75, 80, and 85	5.585	4.599	2.750	0.528	16.75
71, 76, 81, and 86	7.887	4.684	3.028	0.684	18.56
72, 77, 82, and 87	6.764	3.731	2.318	0.537	12.76

Table 3.9 (Cont'd.).

Panel F: Slope Dummies Based on Past Variance Levels[2]

Variance Estimation Period	n	$\hat{\alpha}_{\tau 1}$	$\hat{\alpha}_{\tau 2}$	$\hat{\alpha}_{\tau 3}$	$\hat{\alpha}_{\tau 4}$
(τ-1) to (τ-5)	10185	3.0472 (14.057)	1.1655 (12.541)	1.1697 (19.638)	0.5886 (26.791)
(τ-2) to (τ-6)	9506	1.4055 (9.941)	0.9435 (12.029)	0.9727 (20.030)	0.5961 (24.931)
(τ-3) to (τ-7)	8827	1.2014 (9.657)	0.9024 (11.567)	0.7968 (16.689)	0.6302 (24.293)

[1]The sample period (1968-87) is divided into four equal subperiods. For the 679 sample firms, 2716 subperiod variances are computed for UE. The firm-subperiods are ranked on the variance level, and all observations in a firm-subperiod are assigned to one of four groups based on the subperiod variance ranking. Group 1 (Group 4) represents low (high) variance level. The dummy variable D_g takes a value of one if the firm-year belongs to Group g and zero otherwise. 'n' refers to the number of observations. CAR refers to cumulative market-model abnormal returns from January to December and UE refers to change in income before extraordinary items and discontinued operations per share divided by prior year's stock price.

[2]The number in parentheses is the t-statistic. All slope coefficients are significant at the 0.01 level, one-tailed tests.

[3]$E[\%\Delta\hat{\sigma}^2_\tau(UE)]$ is the sum of $\%\Delta R^2$ and $\%\Delta\hat{\sigma}^2_\tau(CAR)$.

[4]An '&' implies <u>not significant</u> at the 0.05 level, one-tailed tests.

[5]All slope coefficients are significant at the 0.05 level, one-tailed tests.

from one group to the next are also provided (Columns (3), (5), and (7)). The R^2 estimates are obtained from separate regressions conducted for each variance level.[27]

In general, the levels of the three variables increase from the low to the high variance groups. To make inter-group comparisons, I need to isolate the expected increase in σ^2(UE) given the observed increases in R^2 and σ^2(CAR). Given an expectation model, any increase in σ^2(UE) over and above the expected increase can be attributable to measurement error. Assuming a linear relation between two variables y and x, i.e., $y = \alpha x + \epsilon$, the following relation is derived in Appendix B:

$$d\sigma^2(x)/\sigma^2(x) = d\sigma^2(y)/\sigma^2(y) + dR^2/R^2 \tag{3.22}$$

where σ^2 is the variance operator and R^2 is the coefficient of determination between x and y.

To see the intuition behind equation (3.22), consider the scenario where there is a five percent increase in $\sigma^2(y)$ (i.e., $d\sigma^2(y)/\sigma^2(y) = 0.05$) and no change in $\sigma^2(x)$. This implies that the entire increase in $\sigma^2(y)$ is due to an increase in $\sigma^2(\epsilon)$. Given no change in $\sigma^2(x)$, the R^2 should decrease by five percent, thus satisfying equation (3.22). Similarly, if $\sigma^2(y)$ increases by five percent and the R^2 by two percent, then as per equation (3.22), $\sigma^2(x)$ should increase by seven percent. Given the increase in $\sigma^2(y)$, $\sigma^2(x)$ has to increase by five percent to maintain the R^2. However, since the R^2 has increased by two percent, $\sigma^2(x)$ has to increase by seven percent to explain a larger portion of the increased variance in y.

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[27]Since both intercept and slope dummies are used in model (3.21), the parameter estimates from the separate regressions are identical to those reported in Panel A for the pooled regression.

For the present study, the expected percentage change in σ^2(UE) is proxied by the sum of the percentage changes in R^2 and σ^2(CAR). This expected change in σ^2(UE), denoted E[%$\Delta\sigma^2$(UE)], is provided in the last column of Panel B. Comparing Group 2 versus Group 1, given a 136% increase in R^2 and 32% increase in σ^2(CAR), the expected increase in σ^2(UE) is 168%. Since σ^2(UE) actually increased by 453%, it seems that only 37% of the actual increase can be attributed to increased variability in the "true" signal. Similarly for groups 3 and 4, only 19% and 2.6% of the increased variability in unexpected earnings can be explained by changes in R^2 and σ^2(CAR). Note that these estimates should not be construed as point estimates of the "actual" measurement error. They are simply provided to highlight the gravity of the measurement error problem. Overall, the results in Panel B are consistent with a monotonic relation between measurement error and the variability of the unexpected earnings.

The results of estimating model (3.21) on annual samples are provided in Panel C. The near monotonic decline in the earnings response coefficient for each year across the groups is apparent in Panel C. Consistent with Panel A, the magnitude of the annual ERC estimate of Group 4 is similar to that of all firm-years in Table 3.1. However, I observe inter-temporal decline in the group ERCs. For Groups 2-4, this decline is pronounced in the first subperiod. In subperiods 1 and 2, I also observe instability in the ERC estimates of Group 1. Thus, in addition to the variance level, there appear to be other factors affecting the magnitude of the ERC estimates. Furthermore, given the temporal increase in measurement error, the earlier sample years are over represented in the low variance groups and vice versa (see Panel D). For Group 1, the number of firms in the first subperiod (1968-72) is three times the number in the last subperiod (1983–87). For Group 4, the trend is reversed.

To control for these differences, I divide the sample into four subsamples such that each subperiod is equally represented in the subsamples. Specifically, the first subsample is comprised of the observations from the first year of each of the subperiods (i.e., 1968, 1973, 1978, and 1983), and so on. The regression model (3.21) is estimated for each subsample, and the results are provided in Panel E of Table 3.9. While there is a monotonic decline in the ERC estimates across the variance–level groups, there is no such trend across subsamples. This suggests that after I diversify the uncontrolled sub–period effects, the results are consistent with measurement error being a primary determinant of the cross–sectional ERC.

In the analysis conducted so far, the estimate of σ^2(UE) is based on contemporaneous data, i.e., for each year in the subperiod, it is assumed that the subperiod contemporaneous variance estimate is known. This approach was taken to highlight the role of measurement error given perfect foresight. Specifically, I document how the level and shifts in the level of σ^2(UE) dramatically affect the ERC estimates. From a practical standpoint, this highlights the need for developing models to predict the level and changes in σ^2(UE). While developing such models is beyond the scope of this essay, I provide evidence to indicate how quickly the estimates of σ^2(UE) based on past data become obsolete. Specifically, for each firm at time τ, I obtain an estimate of its σ^2(UE) using observations τ–j to τ–j–4, where j = 1, 2, or 3. Each firm–year is assigned to a variance level group using the approach described in Section 3.2.7. For each value of j, the regression model (3.21) is estimated and the results are reported in Panel F.

Though the ERC estimate declines from the low to the high variance group at all three levels of j, the inter-group variability of the ERCs considerably declines as j is increased. The coefficient of variation in the ERCs (not reported) declines by 53% (from 0.718 to 0.339) as j is increased from one to two, and declines by another 9% (to 0.272) as j is increased to three. Thus, the ability of the historical variance to proxy for the current level of measurement error dramatically declines as the forecast horizon is increased from one to two years. It is apparent that the stochastic properties of earnings change are quite dynamic, and therefore, identifying the determinants is critical to understanding the price-earnings relation.

3.2.8 Lead-Lag Relation Between Price and Earnings

There is considerable evidence to support the notion that security prices lead accounting earnings in reflecting economically relevant events (see Beaver, Lambert and Morse [1980], Collins and Kothari [1989], and Kothari and Sloan [1991]). Kothari and Sloan [1991] document that leading years' returns contribute at least as much to the ERC as do the contemporaneous returns. In addition, other studies (e.g., Bernard and Thomas [1989]) have documented significant post-earnings announcement drift in abnormal returns suggesting a delayed price reaction to information in earnings. One interpretation of this finding is the inability of prices to fully reflect the implications of current earnings for future earnings.

It is conceivable that the lead-lag association between price and earnings and the documented differential ERCs across the variance-level groups are partly driven by the same underlying phenomena. For example, Bernard and Thomas [1989] document that the magnitude of the post-earnings announcement drift is related to the magnitude of the unexpected earnings. Given that firms with large magnitudes of unexpected earnings would also have large σ^2(UE), the lower contemporaneous ERC of the high variance group could be explained by failing to control for the delayed reaction of the stock market. On the contrary, one could argue that the stock market can better predict the future prospects of a low variance firm compared to a high variance firm. This implies the ability of prices to lead earnings could also be related to the variance level. In such case, the documented difference in the ERC between the low versus the high variance group may be understated.

To address these issues, I assume that the following model captures the lead–lag components of the ERC:

$$CAR_{i\tau} = \mu_\tau + \sum_{j=-2}^{2} \alpha_{\tau+j} UE_{i\tau+j} + e_{i\tau} \tag{3.23}$$

where $\Sigma\alpha_{\tau+j}$ is an estimate of the total ERC after considering the lead–lag relation between prices and earnings. I estimate this model using the pooled sample data. This model provides a simple approach to quantifying the lead, lag, and contemporaneous components of the ERC. While α_τ captures the contemporaneous price reaction, $\alpha_{\tau+1} + \alpha_{\tau+2}$ ($\alpha_{\tau-1} + \alpha_{\tau-2}$) capture the leading (lagging) price reaction.[28] The choice of a two–year horizon for both the lead and lag components is essentially ad hoc. Since my objective is primarily to look for potential association between the lead–lag components of the ERC and the variance levels of unexpected earnings, I do not attempt to identify the best time horizon to capture the entire

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[28]Since a January to December CAR cumulation period is used, a portion of α_τ ($\alpha_{\tau+1}$) captures the lagging (contemporaneous) price reaction.

lead-lag effect.

To test the relation between the lead-lag components and the variance levels, I estimate the following regression model for the pooled sample:

$$CAR_{i\tau} = \sum_{g=1}^{4}[\mu_{\tau g}D_g] + \sum_{g=1}^{4}[\sum_{j=-2}^{2} \alpha_{\tau+j,g}D_gUE_{i\tau+j}] + e_{i\tau} \qquad (3.24)$$

where the dummy variables (D_g's) represent the variance levels of the unexpected earnings (see model (3.21)). The parameter estimates from this model are presented in Table 3.10. I also provide the estimates of the total ERCs (i.e., $\Sigma\alpha_{\tau+j,g}$) together with each of the lead, lag, and contemporaneous ERCs as a percent of the total ERC. Similar results are presented for the regression model (3.23) in the last two columns of Table 3.10.

Several findings emerge from the results reported in Table 3.10. First, except for the low variance group, the contemporaneous ERCs from the lead-lag regression are very similar to those obtained when the lead-lag terms were excluded from the model (see Panel A of Table 3.9). This indicates that there is no strong correlation between the contemporaneous and the lead-lag earnings changes. Second, while the contemporaneous ERC accounts for about 50% of the total ERC of the extreme variance groups, it represents more than 60% of the total ERC of the two middle groups. Third, consistent with expectations, while the lead ERC contributes to 36% of the total ERC of the low variance group, it captures only 18% of that of the high variance group. The opposite effect is observed for the lag ERC. Compared to 34% for the high variance group, the lag ERC accounts for only 12% of the total ERC for the low variance group. This strong

Table 3.10
REGRESSION OF CUMULATIVE ABNORMAL RETURNS ON LEAD-LAG UNEXPECTED EARNINGS WITH INTERCEPT AND SLOPE DUMMIES FOR VARIANCE LEVELS[1]

$$CAR_{i\tau} = \sum_{g=1}^{4}(\hat{\mu}_{\tau g}D_g) + \sum_{g=1}^{4}\left(\sum_{j=-2}^{2} \hat{\alpha}_{\tau+j,g}D_g UE_{i\tau+j}\right) + e_{i\tau}$$

j	$\hat{\alpha}_{\tau+j,1}$	%	$\hat{\alpha}_{\tau+j,2}$	%	$\hat{\alpha}_{\tau+j,3}$	%	$\hat{\alpha}_{\tau+j,4}$	%	$\hat{\alpha}_{\tau+j}$	%
+2	0.783	9.1	0.499	7.2	-0.018&	-0.5	0.090	5.1	0.137	6.3
+1	2.267	26.5	1.230	17.7	0.806	18.1	0.221	12.5	0.331	15.1
0	4.441	51.9	4.340	62.5	2.828	63.4	0.854	48.6	1.012	46.2
-1	0.711&	8.3	0.386	5.6	0.304	6.8	0.432	24.6	0.489	22.3
-2	0.358&	4.2	0.489	7.0	0.544	12.2	0.162	9.2	0.222	10.1
Sum	8.561	100.0	6.944	100.0	4.464	100.0	1.759	100.0	2.191	100.0

[1]The sample period (1968-87) is divided into four equal subperiods. For the 679 sample firms, 2716 subperiod variances are computed for UE. The firm-subperiods are ranked on the variance level, and all observations in a firm-subperiod are assigned to one of four groups based on the subperiod variance ranking. Group 1 (Group 4) represents low (high) variance level. The dummy variable D_g takes a value of one if the firm-year belongs to Group g and zero otherwise. The analysis is based on 12,710 observations. An '&' indicates that the slope coefficient is <u>not significant</u> at the 0.05 level, one-tailed test. CAR refers to cumulative market-model abnormal returns from January to December and UE refers to change in income before extraordinary items and discontinued operations per share divided by prior year's stock price.

lead (lag) effect explains why the contemporaneous ERC accounts for a lower proportion of the total ERC for the low (high) variance groups. Fourth, while interesting empirical regularities emerge from considering the lead-lag price-earnings relation, none of my inferences are affected by the lead-lag effects. There is a monotonic decline in the total ERC from the low variance to the high variance groups. The total ERC of the low variance group is almost five times as large as the high variance group. Fifth, the ERC components (as well as the total ERC) from the pooled sample are similar in magnitude to those obtained for the high variance group. This once again highlights the dominant effect of the high variance group on the overall sample estimates.

Chapter Four

SUMMARY AND CONCLUDING REMARKS

In this chapter, the purpose of the study, the research hypotheses examined, and the results of the empirical analyses are summarized.

4.1 SUMMARY OF THE FIRST ESSAY

The first essay examines the impact of nonstationarity in earnings on the association between earnings persistence and the earnings response coefficient. To identify this effect, firms were assigned to four groups based on the unit root test statistic such that firms in Group 1 (4) have the highest (lowest) probability of a unit root. Based on this grouping, I hypothesized that the magnitude of correlation between earnings persistence and the earnings response coefficient from a difference (level) stationary model is monotonically decreasing (increasing) from Group 1 to Group 4. I also hypothesized that a difference (level) stationary model would perform better for Group 1 (Group 4) in terms of the significance of association between earnings persistence and the earnings response coefficient.

Based on a sample of 449 firms, the results are generally consistent with my hypotheses, particularly after controlling for measurement error in the earnings response coefficient. The results for the difference stationary model are driven by Group 1 which has the highest probability of a unit root. Consistent with this evidence, time-series properties of earnings indicate that the unit root assumption is valid only for Group 1. When I included the probability of a unit root as an explanatory variable, I was able to explain 50% of the variability in the earnings response coefficient.

My analysis of price-earnings regression statistics indicates that the probability of a unit root in earnings is positively associated with the strength of the price-earnings regression. Furthermore, comparison of the two time-series models with the random walk model suggests that the random walk model outperforms (is outperformed by) the difference (level) stationary model in terms of the strength of the price-earnings regression.

Since persistence and predictability of earnings are highly associated, I replicate the analyses after controlling for earnings predictability. For the difference stationary model, the correlation between earnings persistence and the earnings response coefficient is driven by the high predictability group; whereas, for the level stationary model, the earnings predictability is not confounding the effects of nonstationarity.

The analysis and empirical results in this paper extend the existing work on the association between earnings persistence and the earnings response coefficient. First, tests of the time-series properties of earnings suggest that fitting a difference stationary model for earnings is appropriate only for a sub-set of firms. Second, identification of a unit root in earnings significantly improves the association between earnings persistence and the earnings response coefficient. Third, for the difference stationary model, the evidence indicates that because of collinearity, the predictability of earnings confounds the effects of nonstationarity of earnings as a determinant of the earnings response coefficient. And finally, the strength of the price-earnings regression is positively related to the probability of a unit root in earnings.

4.2 SUMMARY OF THE SECOND ESSAY

This essay provides a econometric framework to link firm-specific ERCs to the "cross-sectional ERC". Such a framework enables me to predict how measurement error affects the inter-temporal stability and the magnitude of the "cross-sectional ERC". Based on these predictions, I show empirically that diversification of the measurement error improves the stability of the cross-sectional ERC and control of the magnitude of measurement error dramatically increases the ERC estimate.

The empirical analysis is conducted based on a sample of 679 December fiscal-year firms for the period 1968-1987. As in Rayburn [1986], I observe a monotonic decline in the annual ERC estimate during the sample period, which is consistent with a temporally increasing measurement error in the firm-specific unexpected earnings. To test this argument, I divide the sample period into four equal subperiods and identify firms with increasing variance of unexpected earnings across subperiods. Based on the number of variance increases, I assign firms into one of four groups such that firms with no (three) variance increases are assigned to Group 1 (Group 4). Consistent with the measurement error argument, I find no strong trend (a temporally declining trend) in the firm-specific ERC estimates of Group 1 (Group 4).

I use the subperiod variance as a proxy for the absolute level of measurement error, and assign each firm-year to one of four groups based on their relative rank on the subperiod variance. While the ERC estimates of the low variance group is almost six, that of the high variance level group is less than one. In addition, the annual ERC estimates of the full sample closely follows those of the high variance level group (one fourth of the sample) indicating the dominant effect of this group. I also document that only a small portion of the change in the variance of unexpected earnings from one variance level group to the next can be attributed to "true signal" in unexpected earnings.

The findings from this essay are important given the concern about both the low magnitude and the inter-temporal instability of earnings response coefficient (see Lev [1989]). The importance of controlling for measurement error in price-earnings studies becomes clear given the dominant role of such measurement error as documented in this essay. Investigation of the firm-specific determinants of measurement error will be a fruitful goal of future research in this area. Examination of the firm-specific financial statement variables, such as the variables measuring the 'quality of earnings' (see Lev and Thiagarajan [1990]), which are correlated with the sources of measurement error, are likely to provide improved understanding of the price-earnings relation.

APPENDICES

APPENDIX A

PROCEDURE FOR COMPUTATION OF THE UNIT ROOT TEST STATISTIC

In this Appendix, the procedure used for computing the unit root test statistic, $Z(t_a)$, is outlined. For each firm in the sample, the following OLS regression is conducted:

$$I_t = \mu + b\cdot(t - n/2) + a\cdot I_{t-1} + u_t \tag{A1}$$

with (n+1) time-series observations in I_t.

Let $X = (\underline{e}, \underline{t}, \underline{I}_{-1})$ with $\underline{e} = (1,\ldots,1)_{n\times 1}$, $\underline{t} = (1 - n/2, 2 - n/2, \ldots, n/2)$, $\underline{I}_{-1} = (I_0, I_1, \ldots, I_{n-1})$ and $\underline{I} = (I_1, I_2, \ldots, I_n)$. The OLS t-statistic t_a is computed as follows:

$$t_a = (a - 1)/(S^2\cdot C_3)^{1/2} \tag{A2}$$

where

$$S^2 = n^{-1}\sum_{t=1}^{n} (I_t - \mu - b\cdot(t - n/2) - a\cdot I_{t-1})^2 \tag{A3}$$

and C_i is the i-th diagonal element of the matrix of $(X'X)^{-1}$.

The transformed statistic $Z(t_a)$ is defined below:

$$Z(t_a) = (S_u/S_{n\ell})\cdot t_a - (n^3/(4\cdot 3^{1/2}\cdot D_X^{1/2}\cdot S_{n\ell}))\cdot(S^2_{n\ell} - S^2_u) \tag{A4}$$

where D_X denotes the determinant of $(X'X)$.

In (A4), S_u and $S_{n\ell}$ are the consistent estimators of $\sigma^2_u = \lim n^{-1}\Sigma E(u^2_t)$ (given by the sample analogue) and $\sigma^2 = \lim n^{-1}E(S^2_n)$ respectively where $S_n = \Sigma u_t$. The estimator used for $S_{n\ell}$ is:

$$S^2_{n\ell} = n^{-1}\sum_{t=1}^{n} u^2_t + 2n^{-1}\sum_{\tau=1}^{\ell}\sum_{t=\tau+1}^{n} u_t\cdot u_{t-\tau}\cdot\omega_{\tau\ell} \tag{A5}$$

where ℓ is chosen corresponding to the maximum order non-zero correlation in the disturbances.

When $\omega_{\tau\ell}$ equals one for all τ and ℓ, Phillips [1987] has shown that

(A5) is a consistent estimator of σ^2 under a wide variety of behavior of u_t. Following a suggestion of Perron and Phillips [1986], the method of Newey and West [1987] was implemented by choosing $\omega_{\tau\ell} = 1 - (\tau/(\ell + 1))$ in order to guarantee a positive estimate of the disturbance variance.

APPENDIX B

RELATION BETWEEN THE VARIANCE OF DEPENDENT AND INDEPENDENT VARIABLES

Within a univariate regression model, the effect of change in the variance of the independent variable is derived as a function of the change in the variance of the dependent variable and the coefficient of determination. Consider the following linear regression model:

$$y = \alpha x + \epsilon \tag{B1}$$

The coefficient of determination (denoted R^2) between y and x is given by:

$$R^2 = COV(y,x)^2/[\sigma^2(x)\sigma^2(y)] \tag{B2}$$

where COV and σ^2 are the covariance and variance operators respectively.

Substituing for y and cancelling terms, we have

$$R^2 = \alpha^2\sigma^2(x)/[\alpha^2\sigma^2(x) + \sigma^2(\epsilon)] \tag{B3}$$

Consider a small change in the R^2,

$$dR^2 = [\partial R^2/\partial\sigma^2(x)]d\sigma^2(x) + [\partial R^2/\partial\sigma^2(\epsilon)]d\sigma^2(\epsilon) \tag{B4}$$

Substituting $d\sigma^2(y) - \alpha^2 d\sigma^2(x)$ for $d\sigma^2(\epsilon)$, we have the following:

$$dR^2 = [(\partial R^2/\partial\sigma^2(x)) - \alpha^2(\partial R^2/\partial\sigma^2(\epsilon))]d\sigma^2(x) + (\partial R^2/\partial\sigma^2(\epsilon))d\sigma^2(y) \qquad \text{(B4)}$$

From (B2), we have the following expressions for the two partial derivatives in (B4):

$$\partial R^2/\partial\sigma^2(x) = \alpha^2\sigma^2(\epsilon)/[\alpha^2\sigma^2(x) + \sigma^2(\epsilon)]^2 \tag{B5}$$

$$\partial R^2/\partial\sigma^2(\epsilon) = -\alpha^2\sigma^2(x)/[\alpha^2\sigma^2(x) + \sigma^2(\epsilon)]^2 \tag{B6}$$

Substituting (B5) and (B6) into (B4), we have

$$dR^2 = [\alpha^2/\sigma^2(y)][d\sigma^2(x) - (\sigma^2(x)/\sigma^2(y))d\sigma^2(y)] \tag{B7}$$

We can rewrite (B7) by substituting $COV(y,x)/\sigma^2(x)$ for α.

$$dR^2 = R^2[(d\sigma^2(x)/\sigma^2(x)) - (d\sigma^2(y)/\sigma^2(y))] \tag{B8}$$

Dividing both sides by R^2 and rearranging terms, we have

$$d\sigma^2(x)/\sigma^2(x) = d\sigma^2(y)/\sigma^2(y) + dR^2/R^2 \tag{B9}$$

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