The Pennsylvania State University

The Graduate School

The Mary Jean and Frank P. Smeal College of Business Administration

IS THE VALUE RELEVANCE OF EARNINGS REALLY DECREASING OVER TIME

A Thesis in

Business Administration

by

Chunlin Mao

Submitted in Partial Fulfillment
of the Requirements
for the Degree of

Doctor of Philosophy

August 2006

The thesis of Chunlin Mao was reviewed and approved* by the following:

James C. McKeown
The Mary Jean and Frank P. Smeal Chaired Professor of Accounting
Thesis Advisor
Chair of Committee

Orie E. Barron
Associate Professor of Accounting

Karl A. Muller
Associate Professor of Accounting

Arun Upneja
Associate Professor of Hospitality Management

Dan Givoly
Ernst &Young Professor of Accounting
Chair of the Department of Accounting

*Signatures are on file in the Graduate School

Is the Value Relevance of Earnings Information Really Decreasing Over Time?

ABSTRACT

Previous studies state that the value relevance of earnings information has declined over time, based on decreasing ERCs and R^2s. This paper demonstrates that measurement error bias is a major factor that drives these results when using earnings changes as a proxy for unexpected earnings. The variance of measurement error in earnings changes as a proxy for unexpected earnings is found to increase over time using a latent variable model. After controlling for the impact of measurement error, trends of ERCs and R^2s estimated using the model are significantly closer to zero and in fact not significantly different from zero. Consistent with these results, the analysis with quarterly earnings, firm-specific models, as well as OLS estimation using analyst forecasts does not provide any evidence of declining value relevance of earnings information over time.

This paper provides an explanation for the low magnitude of OLS ERCs observed in previous literature by showing substantial measurement errors in using either earnings changes or analyst forecasts to calculate unexpected earnings. After controlling for measurement errors with a latent variable model, this paper considerably improves ERC estimation and makes it economically more reasonable.

By "observing" the properties of (unobservable) market earnings expectations, future research, using the latent variable model, allows analysis of a number of accounting research topics from new perspectives.

TABLE OF CONTENTS

LIST OF APPENDIX A: FIGURES

LIST OF APPENDIX B: TABLES

APPENDIX C: LIST OF MODELS

ACKNOWLEDGEMENTS

It has been a unique and exciting journey to prepare this dissertation, which would be impossible without the help, support and encouragement from my family, committee members, and faculties of Penn State University.

For the past six years, my husband, Lei Sun, has constant confidence and patience in me throughout the entire study. Without his encouragement, support and love, it would not be possible to get here. My deepest appreciation is attributed to him. I also appreciate my parents, my sister, my brother and my parents-in-law for their truly understanding and standing behind me. Their encouragement and support always inspire me.

My greatest debt is owed to Jim McKeown for his intensive guidance and support during my study at Penn State. His enthusiasm and expertise in accounting research, which has influenced my entire study, are greatly appreciated. I would also like to thank my excellent thesis committee—Orie Barron, Karl Muller and Arun Upneja, for their immeasurable advice and guidance through the preparation of this thesis.

My special appreciation also goes to Bin Ke, Dan Givoly, Paul Fischer, Henock Louis as well as other faculty members of the Accounting Department for their help and support.

There are many people and things should be acknowledged but are not mentioned here. I am grateful to what I have got from life, from Penn State, and from the people that I love.

1. Introduction

Using a latent variable model, this paper investigates whether previous evidence of declining value relevance of earnings is driven by measurement error bias. Previous studies (e.g., Collins et al. (1997), Nwaeze (1998), Francis and Schipper (1999), Lev and Zarowin (1999), Ely and Waymire (1999), Core et al. (2003) and Kothari and Shanken (2003)) have addressed the concern that earnings information has lost a significant portion of its relevance for investors. Their conclusions are mainly based on the evidence of decreasing earnings response coefficients (ERCs) and R^2s from annual cross-sectional regressions of stock returns or prices on the changes or levels of annual earnings. The researchers argue that the shift from a traditional industrialized economy to a high-tech, service-oriented economy has caused earnings information less useful to the investors. In particular, they show the decline of value relevance to be partially driven by the increasing influence of negative earnings, special earnings items, intangible assets, and high-tech firms, which accompany the shift in the economy.

However, value relevance is just one way to measure the usefulness of earnings to investors, and the evidence of other methods to measure the usefulness of earnings is inconsistent with these valuation studies. For example, Kim and Kross (2005) find that the ability of using earnings to forecast future cash flows increases over time. Francis and Schipper (1999) find that the portfolio returns based on earnings information do not decline over time. Therefore, I am motivated by these studies to reexamine these value relevance studies and raise the question whether the value relevance of earnings is really decreasing over time.

One major criticism of these valuation studies is that they are susceptible to measurement error bias problems when regressing stock returns on the market's unexpected earnings (e.g., Skinner (1996) and Lo and Lys (2001)). Specifically, as the market's earnings expectations are unobservable, measurement error in the proxy for unexpected earnings confounds the OLS estimation and biases both OLS ERC and R^2 towards zero. Annual earnings changes are generally used as a proxy for unexpected earnings in these valuation studies to examine the time trend in value relevance of earnings. With the development of Internet techniques and information markets, however, investors have more timely access to other information resources such as conference calls, press releases, and analyst forecasts and therefore, are less likely to rely on historical earnings information to forecast future earnings. As a result, measurement error in annual earnings changes as a proxy for unexpected earnings is likely to increase over time. Because measurement error biases ERC and R^2 towards zero, the previous evidence of declining value relevance of earnings is likely to be at least partially driven by increasing measurement error bias over time.

In the econometrics literature, Zellner (1970), Goldberger (1972), and Maddala and Nimalendran (1995) have suggested latent variable models to handle measurement error bias problems caused by unobservable variables. Following these studies, I construct a latent variable model to examine the time trend of value relevance of earnings information. Specifically, I set up an identified system, which treats the unobservable market's earnings expectations as a latent variable, to calculate explicitly unknown variables including ERC, R^2, variance of measurement error in the proxies for unexpected earnings, and variance of unexpected earnings.

Because the latent variable model separates ERC from measurement error by treating them as two different unknowns, estimate of the ERC of this model is consistent and expected to be larger than OLS ERC. Empirical analysis of this paper confirms that the magnitude of the latent variable model's ERCs is much larger than that of OLS ERCs on both cross-sectional and firm-specific bases. Moreover, the latent variable model's ERCs have higher associations with ERC determinants implied by a discounted net present value of earnings valuation model, indicating the latent variable model's ERCs are more accurate and economically more reasonable than OLS ERCs.

I examine the time trend of value relevance of earnings with both annual data and quarterly data. Because the previous studies of time trend of value relevance of earnings all use annual data assuming the market expectation of earnings is last year's earnings, I first analyze with annual data from 1963 to 2004 and find that the variance of measurement error in this random walk proxy increases over time. Trends of ERCs and R^2s are significantly closer to zero and in fact not significantly different from zero. These results imply that measurement error bias is a major factor driving the results in previous studies. After controlling for the impact of measurement error, the latent variable model provides no evidence of declining value relevance of earnings information over time.

For the period 1984 to 2004, I also examine the impact of measurement error bias in previous studies by using analyst forecasts instead of earnings changes to calculate unexpected earnings in OLS regressions. Consistent with the results of the latent variable model, the ERCs are not significantly correlated with time. The time trend in R^2s is significantly closer to zero than that in previous studies, but still significantly decreases over time. Using the latent variable model, I find the variance of measurement error in analyst forecasts also increases over time. Therefore, OLS regressions estimated with analyst forecasts are affected by measurement error bias too.

This study further examines the time trend of value relevance of earnings with quarterly data. Although all the previous studies of time trend of value relevance of earnings rely on annual data, analysis using quarterly data provides additional evidence in this issue with more powerful tests. Consistent with the results of annual analysis, I do not find any evidence that value relevance of earnings decreases over time.

The previous studies of time trend of value relevance are all on a cross-sectional basis. However, Kormendi and Lipe (1987), Easton and Zmijewski (1989), and Collins and Kothari (1989) suggest that cross-sectionally estimated ERCs are noisy based on the evidence that ERCs differ greatly among firms. Moreover, Teets and Wasley (1996) recommend that firm-specific models should be used in ERC studies because ERCs estimated with pooled models are biased downward. Based on these studies, I also conduct the test on a firm-specific basis to estimate the time trend of value relevance of earnings more accurately. For each firm, I estimate ERCs and R^2s separately for an old period and a new period using both OLS regressions and the latent variable model. Consistent with the cross-sectional results, both the ERCs and R^2s of the latent variable model are significantly larger than those of the OLS estimation based on random walk proxies. After controlling for measurement error bias with a latent variable model, there is no evidence that value relevance of earnings decreases over time.

This paper makes several contributions to existing knowledge. First, this paper finds that measurement error bias is a major factor driving the previous evidence of declining value relevance of earnings over time. Caution needs to be exercised when comparing OLS ERCs and R^2s across time because of the existence of increasing measurement error bias for OLS regressions estimated using either earnings changes or analyst forecasts.

Second, this paper provides an explanation for the low magnitude of OLS ERCs observed in previous literature by showing substantial measurement errors in using either earnings changes or analyst forecasts to calculate unexpected earnings. It suggests that measurement error bias, not merely poor earnings quality (e.g., Lev (1989)), nonlinearity and other specification problems (e.g., Cheng et al. (1992) and Freeman and Tse (1992)), or cash flow uncertainty (e.g., Imhoff and Lobo (1992)) explains the small OLS ERCs. ERCs estimated using a latent variable model, which controls for measurement error, are economically more reasonable.

Finally, the latent variable model provides unique approaches for examining broad issues in capital market accounting research, by "observing" the properties of the market's earnings expectations. For example, variance of the market's unexpected earnings provides a comprehensive and direct measure of investors' information environment and can be used in contexts such as Regulation FD. Additionally, one can use the variances of measurement errors in different earnings forecasts to analyze how investors incorporate these earnings forecasts into their earnings expectations. Moreover, this paper's latent variable model provides a general method for latent variable model of market expectations. Similar to the model in this paper, a latent variable model of the market's expectation of accruals can also be constructed and it sheds light on research about abnormal accruals as well as earnings management.

The rest of the paper is organized as follows: Section 2 identifies the measurement error bias problems in previous studies and proposes hypotheses. To overcome measurement error bias problems, Section 3 proposes a latent variable model. Section 4 describes the empirical results of annual data as well as sensitivity analyses. Section 5 describes the empirical results of quarterly data. Section 6 draws conclusions and discusses future applications of the latent variable model.

2. Measurement Error Bias Problems and Hypotheses

One major approach in the literature to examine the time trend of value relevance of earnings information is to regress stock returns on annual earnings changes, assuming that previous earnings are the market's earnings expectations and annual earnings changes are the unexpected earnings. [1] Decreasing R^2s and ERCs of cross-sectional annual regressions indicate declining value relevance of earnings information. Lev and Zarowin (1999) and Francis and Schipper (1999) use this approach and find value relevance of earnings decreasing over time.

The use of previous earnings as a proxy for the market's earnings expectations stems from the research in the 1970s (e.g., Albrecht et al. (1977) and Watts and Leftwich (1977)), from which contemporary researchers have concluded that the earnings process can be represented by a random-walk model. But since the 1970s, the economy has changed dramatically with the rise of high-tech industries and changes in business operations. Accounting earnings, which reflect the economy at the firm level, have also changed. Specifically, R&D expenditures, restructuring costs, and intangible assets have become more important in accounting. As the time-series properties of earnings are affected by these changes in accounting earnings, they are also likely to change over time. Consistent with these changes, Mao and McKeown (2005) find more recently earnings are less likely to follow a random-walk process, implying that measurement error for using annual earnings changes as a proxy for unexpected earnings increases over time. If the other aspects of the OLS regression remain the same, increasing magnitude of measurement error will bias the OLS ERCs further downward.

---

[1] Some studies also use a levels regression approach, regressing stock price on earnings levels, but the changes regression approach is generally preferred (e.g., Easton (1999)) because the levels regression approach is susceptible to correlated omitted variable problems and scale problems.

Previous studies provide some explanations for the declining return-earnings association, but these explanations may also be partially driven by measurement error bias problems. For example, Lev and Zarowin (1999) explain that the declining value relevance of earnings partially results from dramatic business changes in the economy of the last two decades and the increasing R&D investment associated with these changes. To support their arguments, Lev and Zarowin (1999) show that ERCs and R^2s of high-tech firms and firms with large amounts of R&D decrease more over time. They, however, ignore the fact that it is more difficult to measure the market's expectation of earnings for these firms, so measurement error is likely to be larger accordingly. As a result, increasing measurement error bias might drive at least part of the decreases in ERCs and R2s they find.

Some other studies explain the decline of value relevance of earnings information with changes in investors' information environment. For example, Ryan and Zarowin (2003) show that earnings increasingly reflect news with a lag relative to stock prices. They explain that the increasing lags could reflect the increasing limitations of the historical cost valuation basis that underlies the current accounting system or the use of more timely non-earnings information for valuation purposes. Basically, they interpret the increasing lags as investors' loss of interest in earnings information. However, the increasing lags could also be explained by a more accurate earnings expectation story. That is, with more timely and better earnings information, investors have more accurate earnings expectations and rely less on a naïve random walk forecast model. As a result, the differences between random walk model earnings forecasts and the market's earnings expectations become larger over time. Therefore, measurement error might contribute to the declining ERCs and R^2s in the previous studies.

Analysis of previous studies suggests that further research requires more refined econometric techniques. Responding to this requirement, I use a latent variable model to control for measurement error bias. Based on the analysis of measurement error bias problems just stated, Hypotheses 1 and 2 follow as:

H1: After controlling for measurement error bias, ERCs decrease less over time than the OLS ERCs estimated with annual earnings changes.

H2: After controlling for measurement error bias, R^2s decrease less over time than the OLS R^2s estimated with annual earnings changes.

The latent variable model also provides a measure of the variance of unobservable measurement error in proxies for unexpected earnings. Therefore, in Hypothesis 3, I examine directly the time trend of measurement error in annual earnings changes as a proxy for unexpected earnings, which provides further support for the first two hypotheses.

H3: Measurement error in annual earnings changes as a proxy for unexpected earnings increases over time.

3. The Latent Variable Model

3.1 Structure of the Latent Variable Model

Suppose F_1 and F_2 are two forecasts of firm i's earnings E. The unobservable market's expectation of earnings F^* is the latent variable in this model. F_1 and F_2 are composed of information available to investors when F^* is generated. Because F_1, F_2, and F^* are all forecasts of earnings E, F_1 and F_2 are regarded as proxies for F^* in the following linear function:

$$F_1 = a_1 + b_1 F^* + \varepsilon_1 \quad (1)$$

$$F_2 = a_2 + b_2 F^* + \varepsilon_2 \quad (2)$$[2]

where a_1 and a_2 are intercepts. b_1 and b_2, as slope coefficients, represent the correlation between F_1, F_2, and F^*. ε_1 and ε_2 are independent of F^*, representing the part of F_1 and F_2 that is not incorporated into F^*. F_1 and F_2 are constructed with different information resources of earnings using different forecasting approaches, so that ε_1 and ε_2 are uncorrelated with each other.

Based on F_1 and F_2, I construct a latent variable model with the following four equations:

$$RET = \beta UE + e \quad (3)$$

$$E = F^* + UE \quad (4)$$

$$E - F_1 = UE - a_1 + (1 - b_1)F^* - \varepsilon_1 \quad (5)$$

$$E - F_2 = UE - a_2 + (1 - b_2)F^* - \varepsilon_2 \quad (6)$$

Equation 3 states a linear relationship between stock returns and unexpected earnings.[3, 4] RET is stock returns over the window from the time of the market's

---

[2] Notice that measurement error in F_1 and F_2 as a proxy for the market's earnings expectations F^* is $-a_1 + (1-b_1)*F^* - \varepsilon_1$ and $-a_2 + (1-b_2)*F^* - \varepsilon_2$, respectively. The forecast error in F_1 and F_2 is $E - F_1$ and $E - F_2$, respectively. The latent variable model aims to estimate ERC more accurately by constructing F_1 and F_2 such that $COV(\varepsilon_1, \varepsilon_2)$ equals zero. Because the model is not supposed to provide a better proxy for the market's earnings expectation F^* or a better forecast of earnings E, the magnitude of the measurement errors and the forecast errors only affects the performance of the model through its impact on $COV(\varepsilon_1, \varepsilon_2)$.

[3] Studies of the return-earnings relationship generally include an intercept in regressing stock returns on unexpected earnings. Omission of an intercept in Equation 3 does not, however, affect the variance-covariance matrix discussed next in this section.

[4] A linear model might not be the best model for the return-earnings relation, since previous studies find return-earnings relationship is nonlinear. But a linear model is used in the previous studies of time trend of value relevance of earnings information. To be consistent with these studies, I also use a linear model here.

earnings expectation F^* to the time of the earnings announcement of E. UE is unexpected earnings. β is ERC. And e is a random noise and uncorrelated with UE.

Equations 4, 5 and 6 construct three relations about the unexpected earnings UE. In Equation 4, by definition earnings E equal the market's earnings expectation F^* plus the market error UE. Equations 5 and 6 are obtained by subtracting Equations 1 and 2 from Equation 4.[5] Since F_1 and F_2 are composed of information available to investors before the return window of RET, one can assume that investors incorporate this information in forming their earnings expectations F^*. Therefore, unexpected earnings UE and random noise e in stock returns are uncorrelated with F_1 and F_2, and accordingly, uncorrelated with ε_1 and ε_2.

Based on Equations 3 to 6, I construct the variance-covariance matrix with the four observable variables RET, E, $E-F_1$, and $E-F_2$. The matrix is composed of eight covariance equations with eight unknown variables: β, b_1, b_2, $VAR(\varepsilon_1)$, $VAR(\varepsilon_2)$, $VAR(e)$, $VAR(F^*)$, and $VAR(UE)$.[6] Therefore, the system is exactly identified, and one can calculate the unknown variables as a function of the matrix's covariance information.[7]

The variance-covariance matrix and the equations of the eight unknown variables in the model are listed in Appendix A. The expressions for ERC, R^2 and variance of measurement error in market expectation proxies are also listed in Appendix A.

---

[5] In Equations 5 and 6, $E-F_1$ and $E-F_2$ can be regarded as proxies for UE. The corresponding measurement errors in $E-F_1$ and $E-F_2$ are $-a_1+(1-b_1)*F^*-\varepsilon_1$ and $-a_2+(1-b_2)*F^*-\varepsilon_2$ respectively.

[6] Note that there are ten covariance equations in total in the variance covariance matrix, but only eight of them can be used because $Cov(E-F_1, F_{1t})$ and $Cov(E-F_2, F_2)$ are redundant information.

[7] As the sample estimates of the variance-covariance matrix are consistent estimates of the population parameters, eight unknown variables can be estimated by setting the sample estimates equal to the population variance-covariance elements.

The model's purpose is to calculate ERC and other unknown variables directly by matching the number of covariance equations with the number of unknown variables in the matrix. The multiple indicators: E, $E-F_1$, and $E-F_2$ of the latent variable UE are specifically constructed in the model to achieve this purpose. For example, the three-by-three variance-covariance matrix of RET, $E-F_1$, and $E-F_2$ is an underidentified covariance equation system, which contains eight unknown variables in five covariance equations. Adding the earnings information E identifies the covariance equation system by providing three new covariance equations: $VAR(E)$, $COV(E,E-F_1)$, and $COV(E,E-F_2)$, without introducing any new unknown variables.

3.2 Comparison Between OLS Regression and the Latent Variable Model

The ERC estimated with the latent variable model is defined as a function of the covariance information in the covariance matrix:

$$\hat{\beta}(LV) = \frac{COV(RET,E)}{VAR(E) - COV(E,F_1)COV(E,F_2)/COV(F_1,F_2)} \tag{7}$$

The OLS ERC estimated by regressing stock return RET on an unexpected earnings proxy $E-F_1$ is also defined as a function of the covariance information in the covariance matrix as

$$\hat{\beta}(OLS) = \frac{COV(RET,E-F_1)}{VAR(E-F_1)} \tag{8}$$

Generally, Equation 8 is assumed to be $\dfrac{\beta VAR(UE)}{VAR(UE)+VAR(\varepsilon_1)}$. But by the definition of Equations 3 and 5, Equation 8 equals to:

$$\frac{\begin{array}{c}\beta VAR(UE)+\beta(1-b_1)COV(UE,F^*)-\beta COV\left(UE,\varepsilon_1\right)\\ +COV(e,UE)+(1-b_1)COV(e,F^*)-COV(e,\varepsilon_1)\end{array}}{\begin{array}{c}VAR(UE)+(1-b_1)^2VAR(F^*)+VAR(\varepsilon_1)\\ +2(1-b_1)COV(UE,F^*)+2COV(UE,\varepsilon_1)\end{array}} \tag{9}$$

Therefore, the OLS regression implicitly assumes UE and e to be uncorrelated with ε_1, ε_2, and F^*, which is the same assumption made in the latent variable model. [8]

Since $VAR(\varepsilon_1)$ is always positive, OLS ERC is biased downward under these assumptions. By contrast, the ERC of the latent variable model in Equation 7 is a consistent estimation of the unobservable ERC. [9] Therefore, one would expect latent variable model's ERC to be larger than OLS ERC.

4. Main Tests of Annual Data

The previous studies of time trend of value relevance of earnings all use annual data. To examine the impact of measurement error on the previous studies, the main tests of this study also use annual data, including annual earnings and annual return windows.

I conduct tests of annual data for two periods: one long period, 1963 to 2004; and one short period, 1984 to 2004. In these two periods, I estimate the latent variable model with different choices of earnings forecasts of F_1 and F_2. In the long period, 1963 to

---

[8] Defining OLS ERC as $\frac{\beta VAR(UE)}{VAR(UE)+VAR(\varepsilon_1)}$ implicitly assumes both UE and e to be uncorrelated with ε_1 and ε_2 and b_1 to be 1. The assumption that b_1 equals 1 is, however, unlikely to be true if investors do not totally believe in F_1. Then the latent variable model has more realistic assumptions, since it does not restrict b_1 to be 1.

[9] The latent variable model's ERC may be biased, if when implementing the model, if F_1 and F_2 do not satisfy the assumption $COV(\varepsilon_1,\varepsilon_2) = 0$. But as $COV(\varepsilon_1,\varepsilon_2)$ is expected to be positive, the latent variable model's ERC is also biased downward. Therefore, if the latent variable model's ERC is larger than OLS ERC, at least we can draw the conclusion that the latent variable model's ERC is less biased than the OLS ERC.

2004, F_1 is a time-series forecast (F_{TS}; details are in Appendix B) and F_2 is a component forecast (F_{CF}; details are in Appendix C), which is an earnings forecast based on previous year's earnings components such as cash flows and accruals. To meet the requirement that measurement error ε_1 is uncorrelated with ε_2, I construct the time-series forecast F_{TS} and the earnings component F_{CF} in different ways: F_{TS} is estimated firm-specifically with a firm's historical earnings, while F_{CF} is estimated cross-sectionally with last year's cash flow and accrual information of each industry.

Because F_{TS} and F_{CF} are both statistical earnings forecasts, measurement errors ε_1 and ε_2 may still be correlated with each other. To improve the performance of the latent variable model, I also construct the model using one statistical earnings forecast: time-series forecast F_{TS} and one judgmental earnings forecast: analyst forecast F_{AN}. Because I/B/E/S analyst forecasts are unavailable before 1984, I conduct the test for the short period from 1984 to 2004.

4.1 Descriptive Statistics

Table 1, Panel A presents the industry distribution of the sample and the average firm size for each industry. I obtain a sample of 252 firms by restricting the data to firms with continuous earnings and earnings component information in Compustat from 1961 to 2004. I need continuous earnings to estimate the firm-specific time-series earnings forecast F_{TS}. As 1963 is the first year when F_{TS} is available, I conduct the test from 1963 to 2004.

Figure 1 presents time trend in forecast accuracy of four earnings forecasts: F_{TS}, F_{AN}, and E_{t-1}. Consistent with Mao and McKeown (2005), forecast errors of a random walk forecast (E_{t-1}) become larger over time. Forecast errors of time-series forecast (F_{TS}) also become larger over time, but the magnitude of their change is much smaller than that in E_{t-1}. By contract, the errors in analyst forecast (F_{AN}) show no clear time trend from 1984 to 2004.

To be consistent with previous studies of the time trend of value relevance of earnings, I begin my data analysis on an annual cross-sectional basis. Table 2 reports the mean of the covariance of the related variables for the periods 1963 to 1983 and 1984 to 2004. The covariance matrix shows that both stock returns and earnings become more volatile and all the covariances become larger for the period 1984 to 2004 than for the period 1963 to 1983. Consistent with the forecast performance in Figure 1, the analyst forecast (F_{AN}) has the smallest forecast error variance and the random walk forecast (E_{t-1}) has the largest forecast error variance. The variance of UE calculated with the latent variable model is not significantly different from the variance of analyst forecast errors.

4.2 Cross-sectional Analysis for the Period 1963 to 2004

In this section, I first estimate the latent variable model on a cross-sectional annual basis with time-series forecast F_{TS} and component forecast F_{CF}. Based on the covariance information, I calculate the latent variable model's ERCs and R^2s according to Equation A3 and A4 in Appendix A. Then for comparison, I replicate previous studies using cross-sectional OLS regressions estimated with previous earnings E_{t-1}. Table 3 shows both the ERCs and R^2s of the latent variable model to be larger than those of the OLS regressions for most years. The medians of the ERCs and R^2s of the latent variable model are 5.18 and 0.25, but those of the OLS regressions are only 1.84 and 0.09, and the differences between them are significantly different from zero. Consistent with the literature of time trend of value relevance of earnings information, Figure 2 (3) shows that OLS ERCs (R^2s) decrease over time. The time trend of the ERCs (R^2s) of the latent variable model is, however, unclear from looking at Figure 2 (3).

In Table 4, Panel A, regressions of the ERCs (R^2s) in Table 3 on a time variable indicate that the decrease in OLS ERCs (R^2s) is statistically significant, whereas the decrease in those of the latent variable model is insignificant. The coefficient of the time variable for the OLS ERCs (R^2s) is smaller than that of the latent variable model — -0.12 (-0.02) for the OLS ERCs (R^2s) vs. -0.07 (-0.01) for the ERCs (R^2s) of the latent variable model. The adjusted R^2s of the regressions are much larger for the OLS ERCs (R^2s) than for ERCs (R^2s) of the latent variable model — 0.52 (0.44) for the OLS ERCs (R^2s) vs. 0.04 (0.03) for the ERCs (R^2s) of the latent variable model. These results provide no evidence of any time trend in ERCs (R^2s) of the latent variable model.

To test Hypotheses 1 and 2 about whether the difference in the time trend of these two estimation methods is significant, I use the following stacked regressions:

$$ERC_t = a_1 + a_2 * t + a_3 * D_i * t + e_t ; \qquad (10)$$

$$R^2_t = a_1 + a_2 * t + a_3 * D_i * t + e_t ; \qquad (11)$$

where $t = 0, 1, \ldots 41$, indicating 1963 to 2004 ; and

$D_i = 1$ when using the latent viable model.

In Table 4, Panel B, a_3 in both the stacked regressions is significantly positive, consistent with the first two hypotheses that after controlling for measurement error bias using a latent variable model, ERCs (R^2s) decrease less over time.

Table 3 (Figure 4) also shows the measurement error variance for annual earnings changes $E_t - E_{t-1}$ as a proxy for unexpected earnings, calculated according to Equation

A6 in Appendix A. Over forty-two years, the measurement error variance increases dramatically. Consistent with Hypothesis 3, regressing the measurement error variance on the time variable shows that this increase is statistically significant (Table 4, Panel C). This test provides additional support for the conclusion that measurement error bias is one important factor driving the OLS ERCs downward over time in the previous studies.

4.3 Cross-sectional Analysis for the Period 1984 to 2004

In this section, I use analyst forecasts F_{AN} instead of the previous earnings E_{t-1} to calculate unexpected earnings in OLS regressions. A simple way to reduce measurement error bias is to use a better proxy in the OLS regressions. A number of studies (e.g., Fried and Givoly (1982), Bathke and Lorek (1984), Brown et al. (1987), Brown (1991), and Brown and Kim (1991)) show that analyst forecasts are better proxies for the market's earnings expectations than time-series forecasts because analyst forecasts are more accurate and have higher associations with stock returns. With smaller measurement error bias, OLS ERCs (R^2s) estimated with F_{AN} are expected to decrease less than OLS ERCs (R^2s) estimated with E_{t-1}. Consistent with this expectation, I find the OLS ERCs (R^2s) calculated with F_{AN} to be generally larger than those calculated with E_{t-1}.

OLS estimation with analyst forecasts is, however, also susceptible to measurement error bias. This method still cannot differentiate changes in the value relevance of earnings information from changes in measurement error bias. To overcome these measurement error bias problems, I estimate the latent variable model with the same data for the same time period from 1984 to 2004 based on time-series forecasts F_{TS} and analyst forecasts F_{AN}. I find the latent variable model's ERCs (R^2s) to be significantly larger than OLS ERCs (R^2s) estimated with analyst forecasts (Table 5), suggesting that the impact of measurement error in the analyst forecasts as proxies for the market's earnings expectations is substantial.

The ERCs (R^2s) of the latent variable model based on F_{TS} and F_{AN} in Table 5 are consistent with and a little larger than those of the latent variable model based on F_{TS} and F_{CF} estimated for the same year[10]. The latent variable model is a robust system, as its estimation is consistent and stable when it is constructed with different sets of earnings forecasts.

I test the significance of time patterns using OLS regressions in Table 6, Panel A. Both ERCs and R^2s of the OLS regression with annual earnings changes decrease significantly from 1984 to 2004. OLS ERCs estimated with analyst forecasts do not significantly decrease with time, but OLS R^2s estimated with analyst forecasts still significantly decrease.[11] OLS regressions with analyst forecasts are consistent with the prediction that with a better proxy, the decrease in OLS ERCs becomes smaller because of less measurement error bias.

The OLS regressions with analyst forecasts may, however, still be susceptible to measurement error bias problems. To examine the measurement error bias problem in analyst forecasts, I calculate the variance of the measurement error in analyst forecasts according to Equation A7 in Appendix A. Table 5 shows measurement error in analyst forecasts to be smaller than those of annual earnings changes. But measurement error in

---

[10] Using F_{TS} and F_{AN} is more likely to satisfy the assumption that $COV(\varepsilon_1,\varepsilon_2)$ equals zero for two reasons: first, smaller measurement error in F_{AN} results in smaller $COV(\varepsilon_1,\varepsilon_2)$; second, $COV(\varepsilon_1,\varepsilon_2)$ is smaller when F_{TS} and F_{AN} are from different forecasting methods (statistical forecast vs. judgmental forecast).

[11] As Gu (2004) points out, OLS R^2s are affected by sampling variations of the independent variable even if the OLS coefficient remains the same. Therefore, the time trend of the ERCs and R^2s is not necessarily consistent. The relatively smaller variations in analyst forecast errors may drive the R^2s downward.

analyst forecasts also increases over the twenty-one years, which affects the time trend in OLS ERCs and R^2s. Specifying the reason for increasing measurement error in analyst forecasts extends beyond this study, but it would be worthwhile in the future to explore whether and why investors' reliance on analyst forecasts decreases over time.

In Table 6, Panel A, the coefficients of the time variable for the ERCs and R^2s of the latent variable model are negative, but they are both small and insignificant, which is consistent with the results of the period 1963 to 2004 in Table 4. Overall, the evidence from the latent variable model is inconsistent with previous studies about the decreasing value relevance of earnings information.

In Table 6, Panel B, I test the difference in the time trend among the three models with the following stacked regressions:

$$ERC_t = a_1 + a_2 * t + a_3 * DAN*t + a_4*DLV*t + e_t , \tag{12}$$

$$R^2_t = a_1 + a_2 * t + a_3 * DAN*t + a_4*DLV*t + e_t \tag{13}$$

where t = 0, 1, . . . 41, indicating 1963 to 2004 ; DAN = 1 when the dependent variable is estimated with the OLS regression using analyst forecasts; and DLV = 1 when the dependent variable is estimated with the latent variable model.

In Table 6, Panel B, a significant a_3 in the R^2 regression implies that the difference in the time trend in the two OLS R^2s is significant, but an insignificant a_3 in the ERC regression implies that the difference in the time trend of the two OLS ERCs is insignificant. A significantly positive a_4 in both regressions implies that ERCs and R^2s of the latent variable model decrease less over time than those of the OLS regressions estimated with annual earnings changes. Therefore, these results are consistent with Hypotheses 1 and 2. Table 6, Panel C shows that variance of measurement errors in both annual earnings changes and analyst forecasts increases significantly over time.

4.4 Firm-specific Analysis

For each firm, I estimate ERCs and R^2s separately for the periods 1963 to 1983 and 1984 to 2004 using both OLS regressions and the latent variable model.[12] Table 7 shows that, consistent with the cross-sectional results, both the ERCs and R^2s of the latent variable model are significantly larger than those of the OLS regressions. OLS ERCs and R^2s significantly decrease over two periods. The changes over two periods in the ERCs and R^2s of the latent variable model are small and insignificant. The difference in the changes over the two periods between ERCs (R^2s) of the latent variable model and OLS ERCs (R^2s) is -2.15 (-0.05) and significant, which is consistent with Hypothesis 1 (2) — namely, that after controlling for measurement error bias with a latent variable model, ERCs (R^2s) decrease less over time.

Table 7, Panel B shows that the median firm-specific variances of measurement error in annual earnings changes $E_t - E_{t-1}$ as a proxy for unexpected earnings increase from 2.31 in the period from 1963 to 1983 to 6.67 in the period from 1984 to 2004. The median increase is 4.3. These results further confirm the prediction that investors are less likely to rely on the previous year's earnings to forecast the current earnings over time.

The literature has found that OLS ERCs are smaller for loss firms and high-tech firms. However, it is also likely that OLS ERCs are biased downward for these firms, since it is more difficult to measure the market's expectation of earnings for these firms. Firm-specific variance of the measurement error of the latent variable model estimation is consistent with this conjecture. Table 7, Panel C shows that variance of measurement errors in the random walk proxy increases with the magnitude of R&D of a firm. Panel D

[12] The latent variable model is based on the time-series forecasts and the component forecasts. Because analyst forecasts are unavailable for the period 1963 to 1983, firm-specific estimates of the latent variable model cannot be conducted to examine the time trend of value relevance of earnings information.

shows that the median of the variance of the measurement error in the random walk proxy for loss firms in the old period (new period) is 5.45 (9.38), while that of the profit firms is 1.91 (4.54).

4.5 Sensitivity Checks

My first sensitivity check shows that the latent variable model's ERCs are more consistent with the existing theories than OLS ERCs. Based on a valuation model of discounted net present value of earnings, ERCs should increase in earnings persistence, firm growth and decrease in risk (e.g., Kormendia and Lipe (1987), Easton and Zmijewski (1989) and Collins and Kothari (1989)). Accordingly, these factors can be used to compare the accuracy of ERC estimation. I regress firm-specific ERCs estimated with the latent variable model and OLS regression separately on these 3 factors. Table 8 shows that the sign of the three coefficients are consistent with the discounted net present value of earnings model in both regressions. Because previous studies find that firm size is associated with the magnitude of ERCs, I use total assets as a control variable for firm size in both regressions. Results of the regressions show that the latent variable model's ERCs are more associated with these factors---the R^2 of the regression of OLS ERCs is 0.09, while the R^2 of the regression of the latent variable model's ERCs is 0.27. Therefore, the latent variable model is more accurate and economically more reasonable than the OLS regressions.

My second sensitivity check shows that ERCs and R^2s of the latent variable model have smaller variation. The OLS ERCs and R^2s seem to have smaller variation, but it is because they are biased towards zero. After controlling for scale difference, the latent variable model has smaller coefficient of variation, which is defined as standard deviation deflated by mean. Consistently, the latent variable model also has smaller average absolute percentage change.

My third sensitivity check examines whether controlling for earnings levels in the OLS regression affects the results in this paper. Lev and Zarowin (1999) and Francis and Schipper (1999) control for earnings levels in their OLS regressions as:

$$RET = c_1 + c_2 * (E_t - E_{t-1}) + c_3 * E_t + e_t \tag{14}$$

They define ERC as c_2+c_3 and find both the ERCs and R^2s estimated with Equation 14 decrease over time. According to Equation 14, I estimate ERC and R^2 both firm-specifically and cross-sectionally. These ERCs and R^2s are marginally larger than those of the OLS regressions without any control variable, but still smaller than those estimated with the latent variable model and those of OLS regressions estimated with analyst forecasts. I repeat all the main tests and find them all consistent with the previous results in this paper.

I also assess the sensitivity of this paper's results to alternative specifications of the time-series forecasts F_{TS} and analyst forecasts F_{AN}. The latent variable model requires F_{TS} and F_{AN} to be available to investors before the return windows. To satisfy this requirement, I conduct, for the period from 1984 to 2004, out-of-sample forecasts for F_{TS}. I also use the consensus analyst forecasts of the first month of each year and exclude the first month from the calculation of the annual stock return to ensure that F_{AN} is an *ex ante* forecast. The results of the tests with the new F_{TS}, F_{AN}, and stock returns are all consistent with the previous analysis. [13]

[13] On the other hand, investors incorporate other information besides historical earnings information into their earnings expectation F^*, which cannot be represented by any *ex ante* time-series earnings forecast.

Moreover, the latent variable model assumes that stock returns are uncorrelated with the earnings forecasts F_1 and F_2 (or F_{TS}, F_{CF}, and F_{AN}) used in the model. But without any consensus about market efficiency in the literature, it is unclear whether this assumption is true. To support the use of this assumption, I examine the correlation between stock returns and F_{TS}, F_{CF}, and F_{AN} both on a cross-sectional basis and on a firm-specific basis. The correlations are insignificantly different from zero in all cases. Therefore, stock returns are likely to be uncorrelated with these earnings forecasts in the latent variable model.

Finally, I examine the impact of the assumption that the measurement error ε_1 and ε_2 of F_{TS} and F_{CF} are uncorrelated with each other. It is impossible to measure $COV(\varepsilon_1,\varepsilon_2)$ as the market's earnings expectation F^* is unobservable. But because analyst forecasts of earnings are generally believed to be close to F^*, it is plausible to substitute F^* with analyst forecasts to examine the impact of $COV(\varepsilon_1,\varepsilon_2)$ when component forecast F_{CF} is used as F_2. More specifically, substituting F^* with analyst forecasts F_{AN} in Equations 1 and 2 yields two equations: $F_1 = a'_{i1} + b'_1 F_{AN} + v_1$ and $F_2 = a'_{i2} + b'_2 F_{AN} + v_2$. I estimate $COV(v_1,v_2)$ for the period 1984 to 2004 both on cross-sectional and firm-specific bases. With $COV(v_1,v_2)$ as a proxy for $COV(\varepsilon_1,\varepsilon_2)$, I estimate the latent variable model again. For firm-specific estimation, I assume $COV(\varepsilon_1,\varepsilon_2)$ for the period from 1963 to 1983 to be the same as $COV(\varepsilon_1,\varepsilon_2)$ for the period 1984 to 2004. The results of all the previous tests hold with the new ERCs and R^2s.

Therefore, using future earnings information in the *ex post* time-series earnings forecast may help to approximate F^* better.

5. Tests of Quarterly Data

This study further examines the time trend of value relevance of earnings on quarterly data. The benefit of using quarterly data is that the availability of more quarterly periods enables more powerful tests. Since all the previous studies of time trend of value relevance of earnings rely on annual data, the analysis with quarterly data in this study provides additional evidence in this issue. Quarterly sample is composed of firms with continuous earnings information in Compustat and quarterly analyst forecasts in I/B/E/S from 1984 to 2004. The stock return window is from two days after the previous quarter's earnings announcement to the current quarter's earnings announcement. And all the variables in the estimation are deflated by the stock price at the beginning of the quarter.

Before estimating the latent variable model, I first estimate OLS ERCs with quarterly data both cross-sectionally and firm-specifically to compare their magnitudes with the literature. In the OLS estimation, I use a seasonal random walk proxy and an analyst forecast proxy for the market's expectation of earnings. The cross-sectional ERCs are estimated from the first quarter of 1984 to the fourth quarter of 2004. Firm-specific estimation is conducted over two periods: the first quarter of 1984 to the second quarter of 1994, and the third quarter of 1994 to the fourth quarter of 2004, with 42 firm/quarters in each period. Teets and Wasley (1996) also estimate quarterly ERCs cross-sectionally and firm-specifically with a seasonal random walk proxy for the market's expectation of earnings and a deflator of stock price, the median (mean) of which are 0.04 (0.05) and 0.65 (0.72) respectively. In this study, the medians (means) of the cross-sectional ERCs and firm-specific ERCs are 0.41 (0.53) and 0.88 (0.91), which are comparable to those in

Teets and Wasley (1996)[14]. The reason for the larger cross-sectional ERCs might be caused by the sample in this study being subject to larger survivorship bias.

Teets and Wasley (1996) also demonstrate that firm-specific OLS ERCs equal cross-sectional OLS ERCs only under two conditions. Specifically, if the individual firms' ERCs are identical or if the firm-specific variances of unexpected earnings (UE) are identical. However, they show that both the firm-specific ERCs and the variances of unexpected earnings (UE) differ cross-sectionally. More importantly, they demonstrate a negative association between the firm-specific ERCs and UE variances, which biases cross-sectional OLS ERCs downward.

Consistent with the analysis in Teets and Wasley (1996), the median of firm-specific OLS ERCs is larger than the median of cross-sectional OLS ERCs in Table 11. Specifically, the median of firm-specific OLS ERCs for the period 1984 to 1994 is 1.08, while the median of cross-sectional OLS ERCs for this period is 0.46. The median of firm-specific OLS ERCs for the period 1994 to 2004 is 0.61, while the median of cross-sectional OLS ERCs for this period is 0.32.

To examine the time trend of value relevance of earnings, the latent variable model is also estimated cross-sectionally and firm-specifically for the same period of time. Time-series forecasts F_{TS} and quarterly analyst forecasts F_{AN} are used in the latent variable model because they are more likely to satisfy the model's assumptions. To simplify the estimation of the time-series forecasts, I use the Foster model (Foster (1977)) to estimate F_{TS}. For each firm I estimate the coefficients of Foster model for two periods: the first quarter of 1984 to the second quarter of 1994, and the third quarter of 1994 to the

[14] See Table 9 and Table 11. Teets and Wasley (1996) do not include analysis of R^2, so I cannot make comparison of R^2 here.

fourth quarter of 2004. Then I construct earnings forecast F_{TS} for each quarter. F_{AN} is the median analyst forecast of quarterly earnings made within 15 days after the previous quarter's earnings announcement.

Table 9 shows cross-sectional estimation of the ERCs and R^2s of the latent variable model as well as the OLS ERCs and R^2s estimated with the seasonal random walk proxy and analyst forecast proxy from the first quarter of 1984 to the fourth quarter of 2004. Notice that the ERCs and R^2s estimated with quarterly data are generally smaller than the corresponding ERCs and R^2s estimated with annual data in the previous session of this study. There are two reasons for smaller OLS ERCs and R^2s with quarterly data: first, since quarterly ERCs are estimated over shorter windows, they are smaller than the corresponding annual ERCs under the same conditions; second, the seasonal random walk proxy for the market's expectation of earnings in the quarterly OLS estimation may have larger measurement error bias than the random walk proxy in the annual OLS estimation, so both the quarterly OLS ERCs and R^2 have larger downward bias. And the reason for the smaller latent variable model estimation might be that because F_{TS} is not an accurate earnings forecast, ε_1 of F_{TS} and ε_2 of F_{AN} are positively correlated with each other, resulting in larger downward bias in the estimation. Consistent with the estimation with annual data of this study, the ERCs and R^2s of the latent variable model are of much larger magnitude than those of the OLS estimation with the seasonal random walk proxy. However, the difference between the latent variable model and OLS with analyst forecast proxy is not significant.

Table 10 Panel A shows the statistical tests of the time trend of the value relevance of earnings. The coefficients of the time indicators are not significantly different from zero, which is inconsistent with the decreasing pattern of those of the annual data. At the same time, the ERCs and R^2s estimated with the latent variable model using quarterly data do not significantly decrease over time in Table 10 Panel A. In sum, the cross-sectional estimation using quarterly data provides no evidence that value relevance of earning decreases over time.

In Table 10 Panel B, the variance of the measurement errors of the seasonal random walk proxy in quarterly OLS estimation does not exhibit significant time trend either. As a result, there is no evidence that measurement errors bias quarterly OLS ERCs and R^2s estimated with the seasonal random walk proxy as in the annual OLS estimation. Table 10 Panel B also shows that the variance of the measurement errors of the analyst forecast of quarterly earnings increases significantly over time, which means that the OLS estimation with analyst forecasts is still subject to measurement error bias problems.

Consistent with the cross-sectional analysis of the quarterly data, Table 11 shows that the changes between the two periods in the ERCs and R^2s of both the OLS regression and the latent variable model are small and insignificant. At the same time, the variance of the measurement errors in the seasonal random walk proxy does not change significantly over the two periods, while that of the analyst forecast proxy increases significantly over the two periods. Again, the firm-specific estimation using quarterly data does not provide evidence that value relevance of earnings decreases over time.

6. Conclusion and Future Applications of the Latent Variable Model

Using a latent variable model, this study investigates the popular claim that accounting information has become less value relevant over time. It demonstrates that measurement error bias is a major factor that drives the results in the previous studies by showing that the variance of measurement error in annual earnings changes as a proxy for unexpected earnings to increase over the past forty-two years. After controlling for the impact of measurement error, trends of ERCs and R^2s estimated using the model are significantly closer to zero and in fact not significantly different from zero. As a result, the previous evidence of declining value relevance of earnings may be driven by measurement error bias in OLS regressions.

This study contributes to the literature of time trend of value relevance of earnings in the following aspects. First, the latent variable model substantially reduces the measurement error bias in OLS ERCs and R^2s of the previous studies. On average, ERCs and R^2s estimated with the latent variable model are four to five times the magnitude of OLS ERCs and R^2s estimated with the random walk proxies. This paper's results imply that there is serious downward bias in the OLS ERCs estimated with the random walk proxies especially over the last twenty years. Therefore, caution needs to be paid when using this method to draw any conclusion about comparing the value relevance of earnings either over time or between different types of firms.

Second, while all the previous studies of time trend of value relevance of earnings rely on annual data, this study provides additional evidence in this issue with more powerful tests using quarterly data. I find that ERCs and R^2s of the latent variable model are of much larger magnitude than those of the OLS estimation with the seasonal random walk proxy. However, the difference between the latent variable model and OLS regressing using analyst forecasts is not significant. Consistent with the results of the annual analyses, I do not find the latent variable model's ERCs and R^2s decrease over time. Again, the analysis using quarterly data does not provide evidence that value relevance of earnings decreases over time.

Third, because ERCs estimated with pooled models are biased downward, the previous results of time trend of value relevance of earnings are not accurate since they are all based on cross-sectional analysis. This study makes more accurate estimation of ERCs on a firm-specific basis using both annual period and quarterly period. Consistent with the findings in Teets and Wasley (1996), I find that firm-specific OLS ERCS are larger than cross-sectional OLS ERCs. In the firm-specific analysis, I also find that both the ERCs and R^2s of the latent variable model are significantly larger than those of the OLS estimation based on random walk proxies. After controlling for measurement error bias with a latent variable model, there is no evidence that value relevance of earnings decreases over time.

Fourth, this study also provides additional evidence about the time trend of value relevance of earnings by estimating OLS ERCs and R^2s with a better proxy for the market's expectation of earnings--analyst forecasts of earnings. With smaller measurement error bias, the time trend in OLS ERCs and R^2s estimated with analyst forecasts is significantly closer to zero than that in the previous studies. However, because the variance of measurement error in analyst forecasts also increases over time, using analyst forecasts to estimate OLS ERCs and R^2s cannot solve measurement error bias problems completely.

Examining the measurement error bias problem in the time trend of value relevance of earnings information in this paper represents just one specific application of the latent variable model. This model enables one to "observe" the properties of unobservable market earnings expectations, an essential concept in accounting research. Therefore, future research, using the latent variable model, allows analysis of the following accounting research topics from new perspectives.

First, the latent variable model provides more accurate estimates of ERC in studies of the return-earnings relation. Previous research has found that OLS ERCs are smaller for loss firms and firms with large intangible assets. It is, however, likely that the measurement error bias is larger for firms with losses and large intangible assets because it is more difficult to measure the market's earnings expectations for these firms. With the latent variable model, it becomes possible to examine to what extent previous results are driven by the measurement error bias.

Second, estimates of the variance of unexpected earnings provide direct measures about market forecast accuracy and make it possible to examine whether regulations and firms' disclosure choices affect investors' information in terms of earnings forecast accuracy. Previous research typically relies on stock movement (e.g., stock return volatility, accumulated abnormal returns, or trading volume) to analyze how investors' information is affected by regulations or firms' disclosure choices. The inference about investors' information from stock movement is, however, unclear because stock movement can be influenced by many factors other than investors' information, and it is difficult to fully control them. Some other studies infer investors' information from analyst forecasts. These inferences, however, can be questionable without knowledge of the difference between investors' and analysts' information. Moreover, one cannot use analyst forecasts to proxy for investors' expectations in such contexts as Regulation FD, which affect analysts and investors in different ways. The latent variable model overcomes the weaknesses in these previous measures because the measure of variance of unexpected earnings is more accurate and direct in these contexts.

Third, the latent variable model of this paper provides a general method to construct latent variable models of unobservable market expectations. The same model structure is applicable to macroeconomic issues such as the market's expectation of interest rate, deflation, and GDP. This model can also be used to examine other accounting issues. For example, a latent variable model of the market's expectation of accruals might shed light on investors' responses to abnormal accruals as well as managers' earnings management behaviors.

References

Albrecht, W. S., L. L. Lookabill, and J. C. McKeown. The time-series properties of annual earnings. *Journal of Accounting Research* (1977) 226-44.

Bathke, Jr. A.W., and K.S. Lorek. The relationship between time-series models and the security market's expectation of quarterly earnings. *The Accounting Review (*1984) vol. 59, 163-176.

Brown, L. D. Forecast selection when all forecasts are not equally recent. International *Journal of Forecasting* (1991), vol.7, 349-356.

Brown, L.D., P.A.Griffin, R.L. Haerman, and M.E. Zmijewski. Security analyst superiority relative to univariate time-series models in forecasting quarterly earnings. *Journal of Accounting & Economics* (1987), vol. 9, 61-87.

Brown, L.D., and K.J. Kim. Timely aggregate analyst forecasts as better proxies for market earnings expectations. *Journal of Accounting Research* (1991), vol.29, 382-385.

Cheng, C., S. Agnes, W.S. Hopwood, and J.C. McKeown. Non-linearity and specification problems in unexpected earnings response regression model. *The Accounting Review* (1992), vol. 67, 579-599.

Collins, D., S. P. Kothari, J. Shanken, and R. Sloan. Lack of timeliness versus noise as explanations for low contemporaneous return-earnings association. *Journal of Accounting & Economics* (1994), vol.18, 289-324.

Collins, D., E. Maydew, and I.Weiss. Changes in the value-relevance of earnings and book values over the past forty years. *Journal of Accounting & Economics* (1997), vol.27, 39-67.

Core, J.E., W.R. Guay, and A.VanBuskirk. Market valuation in the new economy: an investigation of what has changes. *Journal of Accounting & Economics* (2003), vol.34, 43-67.

Easton, P. Security returns and the value relevance of accounting data. *Accounting Horizons* (1999), vol. 13, 399-412.

Easton, P., and M., Zmijewski. Cross-sectional variation in the stock market response to accounting earnings announcements. *Journal of Accounting & Economics* (1989), vol. 11, 117-141.

Ely, K., and G. Waymire. Accounting standard-setting orgnizations and earnings relevance: Longitudinal evidence from NYSE common stocks, 1927-93. *Journal of Accounting Research* (1999), vol. 37, 293-318.

Foster, G. Quarterly accounting data: time series properties and predictive-ability results. *The Accounting Review* (1977) vol. 52, 1-21

Francis, J., and K. Schipper. Have financial statements lost their relevance? *Journal of Accounting Research* (1999), vol.37, 319-352.

Freeman, R.N., and S.Y. Tse. A nonlinear model of security price responses to unexpected earnings. *Journal of Accounting Research* (1992), vol.30, 185-209.

Fried, O., and D. Givoly. Financial analysts' forecasts of earnings: A better surrogate for market expectations. *Journal of Accounting & Economics* (1982), 85-107.

Gu, Z. Across-sample incomparability of R^2s and additional evidence of value relevance changes over time. Working Paper (2004).

Goldberger, A.S. Maximum-likelihood estimation of regressions containing unobservable independent variables. *International Economic Review* (1972), vol. 13, 1-15.

Haskins, M., K. Ferris, R. Sack, and B. Allen. (1993) *Financial Accounting and Reporting*. Homewood, IL: Irwin.

Imhoff, E.A., and G.J. Lobo. The effect of *ex ante* earnings uncertainty on earnings response coefficients. *The Accounting Review* (1992) vol. 67, 427-439.

Kieso, D., and J. Weygrandt. (1995) Intermediate Accounting. 8th ed. New York, NY: Jogn Wiley & Sons.

Kim, M., and W. Kross. The ability of earnings to predict future operating cash flows has been increasing—not decreasing. *Journal of Accounting Research* (2005), vol. 43, 753-780.

Kormendi, R., and R. Lipe. Earnings innovations, earnings persistence and stock returns. *Journal of Business* (1987), vol.60, 323-345.

Kothari, S.P., and J. Shanken. Time-series coefficient variation in value-relevance regressions: A discussion of Core, Guay, and Van Buskirk and new evidence. *Journal of Accounting & Economics* (2003), vol.34, 69-87.

Lev, B. On the usefulness of earnings and earnings research: Lessons and directions from two decades of empirical research. *Journal of Accounting Research* (1989), vol. 27, 153-92.

Lev, B., and P. Zarowin. The boundaries of financial reporting and how to extend them. *Journal of Accounting Research* (1999), vol.37, 353-385.

Lo, K., and T. Lys. Bridging the gap between value relevance and information content. Working Paper (2001).

Maddala, G.S., and M. Nimalendran. An unobserved component panel data model to study the effect of earnings surprises on stock prices, trading volumes, and spreads. *Journal of Econometrics* (1995), vol.68, 229-242.

Mao, C., and J.C. McKeown. Does random walk still rule annual accounting earnings? Working Paper (2005).

Nwaeze, E.T. Regulation and the valuation relevance of book value and earnings: evidence from the United States. *Contemporary Accounting Research* (1998), vol. 15, 547-573.

Ryan, S.G., and P.A. Zarowin. Why has the contemporaneous linear returns-earnings relation declined? *The Accounting Review* (2003), vol. 78, 523-553.

Schilit, H. (1993). *Financial Shenanigans.* New York, NY: McGraw-Hill, Inc.

Skinner, D. Are disclosures about bank derivatives and employee stock options "value-relevant"? *Journal of Accounting & Economics* (1996), vol. 22, 393-405.

Sloan, R.G. Do stock prices fully reflect information in cash flows and accruals about future earnings? *The Accounting Review* (1996), vol. 71, 289-315.

Stickney, C. (1993) Financial Statement Analysis: A Strategic Perspective. 2nd ed. Fort Worth, TX: The Dryden Press.

Teets, W., and C. Wasley. Estimating earnings response coefficients: Pooled versus firm-specific models. *Journal of Accounting & Economics* (1996), vol. 21, 279-295.

Watts, R. L., and R.W. Leftwich. The time series of annual accounting earnings. *Journal of Accounting Research* (1977) 253-271.

White, G., A. Sondhi, and D. Fried. (1994) *The Analysis and use of Financial Statements.* New York, NY: John Wiley & Sons.

Zellner, A. Estimation of regression relationships containing unobservable independent variables. *International Economic Review* (1970), vol. 11, 441-454.

Appendix A: Figures

Figure 1: Comparison of Forecast Performance

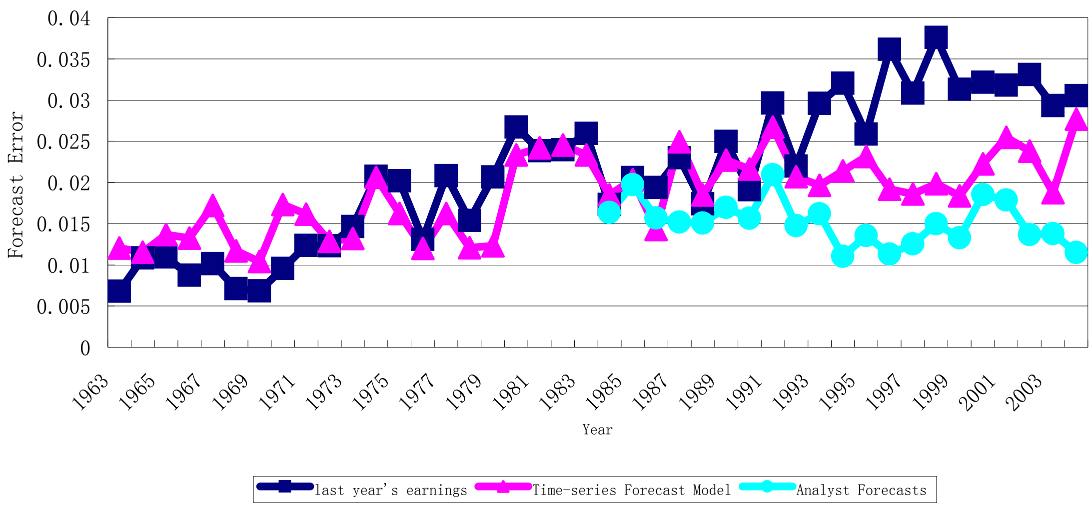


Figure 2: ERC (Annual Data) for Period 1963 to 2004

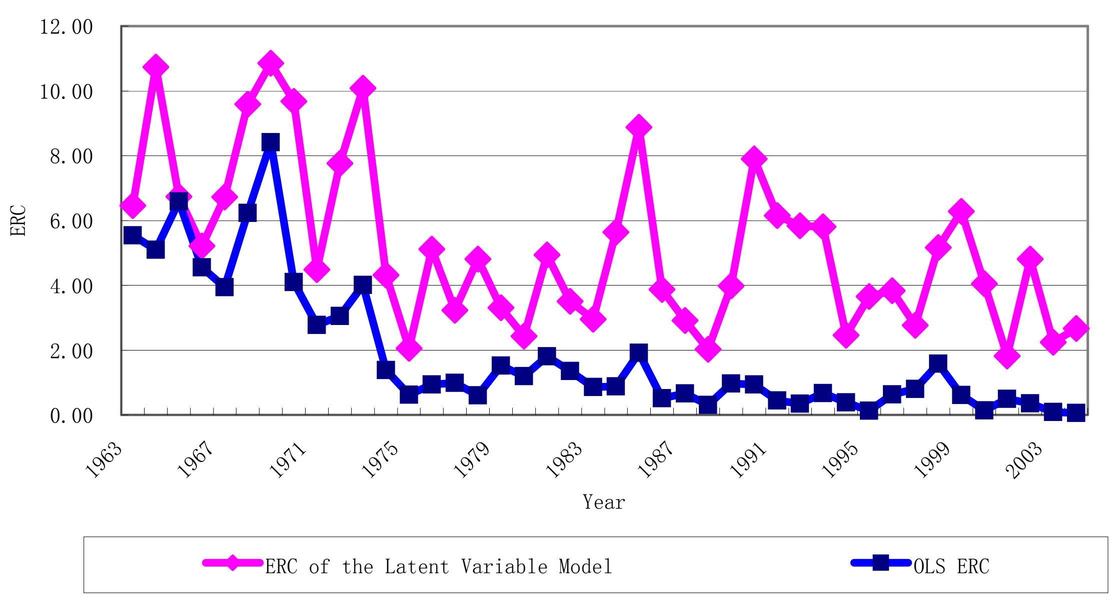


Figure 3: R^2 (Annual Data) for Period 1963 to 2004

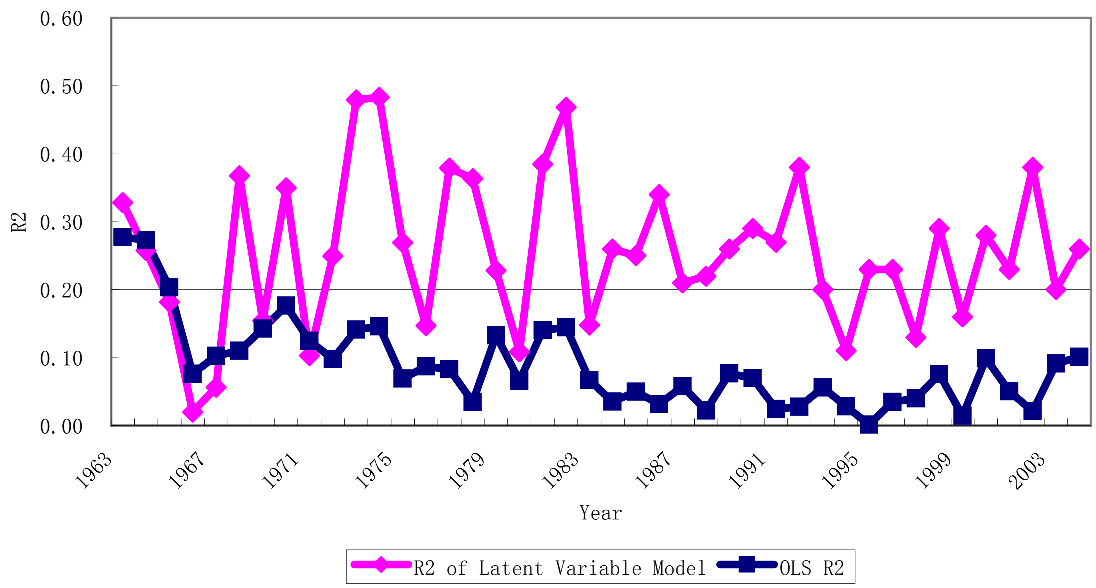
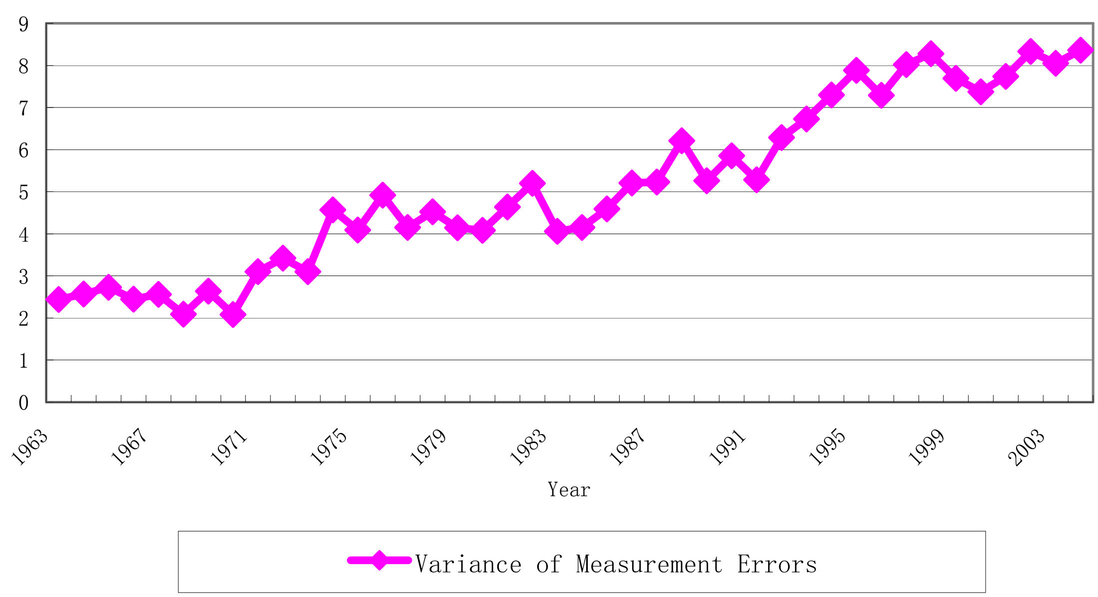


Figure 4: Variance of Measurement Error (Annual Data) for Period 1963 to 2004



Appendix B: Tables

Table 1
Industry Distribution and Firm Size (Assets)

One digit SIC code	Number of firms	Mean assets (millions)
1	13	3,400
2	65	5,978
3	79	5,620
4	66	5,249
5	17	4,060
6	2	14,256
7	6	7,284
9	4	38,347
	Total: 252	Mean: 10,524

Table 2
The Mean Cross-sectional Variance-covariance Information

		RET	E_t	$E_t - F_{TS}$	$E_t - F_{CF}$	$E_t - E_{t-1}$	$E_t - F_{AN}$
RET	1963-1983	85.15	2.45	2.82	3.46	4.87	-
	1984-2004	92.21	7.23	6.74	7.12	7.79	7.64
E_t	1963-1983	-	5.24	2.13	2.21	3.48	-
	1984-2004	-	14.23	5.91	7.16	4.05	6.25
$E_t - F_{TS}$	1963-1983	-	-	2.20	3.44	2.07	-
	1984-2004	-	-	6.13	5.77	8.08	6.10
$E_t - F_{CF}$	1963-1983	-	-	-	2.80	2.76	-
	1984-2004	-	-	-	6.97	6.43	6.42
$E_t - E_{t-1}$	1963-1983	-	-	-	-	3.57	-
	1984-2004	-	-	-	-	7.95	5.92
$E_t - F_{AN}$	1984-2004	-	-	-	-	-	5.82

Notes:
The numbers in Table 2 are multiplied by 1000.
RET : Size-adjusted stock returns of fiscal year. E_t : Current year's EPS. E_{t-1} : Last year's EPS.
F_{TS} : The time-series forecast of E_t . F_{CF} : The component forecast of E_t . F_{AN} : Analyst forecast of E_t . All E_t , E_{t-1} , F_{TS} , F_{CF} and F_{AN} are scaled by the stock price at the beginning of the fiscal year.
*The latent variable model is estimated based on F_{TS} : The time-series forecast of E_t . F_{CF} : The component forecast of E_t .

Table 3

The Cross-sectional Annual Estimation of Variance of Measurement Error (ME), ERC and R^2 with OLS and the Latent Variable Model (1963 – 2004)

	ERC		**R^2**		**ME of E_{t-1}**
Year	**OLS1**	**LV1**	**OLS1**	**LV1**	**LV1**
1963	5.54	6.46	0.28	0.33	2.44
1964	5.09	10.73	0.27	0.26	2.57
1965	6.59	6.74	0.20	0.18	2.73
1966	4.55	5.22	0.08	0.02	2.45
1967	3.94	6.72	0.10	0.06	2.56
1968	6.23	9.59	0.11	0.37	2.09
1969	8.42	10.85	0.14	0.15	2.64
1970	4.09	9.68	0.18	0.35	2.08
1971	2.77	4.48	0.12	0.10	3.10
1972	3.05	7.76	0.10	0.25	3.42
1973	4.01	10.08	0.14	0.48	3.10
1974	1.38	4.31	0.15	0.48	4.57
1975	0.62	2.06	0.07	0.27	4.09
1976	0.94	5.11	0.09	0.15	4.92
1977	0.98	3.23	0.08	0.38	4.15
1978	0.60	4.81	0.04	0.36	4.52
1979	1.52	3.31	0.13	0.23	4.14
1980	1.20	2.43	0.07	0.11	4.08
1981	1.81	4.94	0.14	0.38	4.64
1982	1.36	3.50	0.05	0.47	5.20
1983	0.86	2.95	0.07	0.15	4.06
1984	0.88	5.64	0.14	0.26	4.15
1985	1.92	8.88	0.14	0.25	4.59
1986	0.51	3.87	0.03	0.34	5.21
1987	0.67	2.91	0.06	0.21	5.23
1988	0.31	2.02	0.02	0.22	6.21
1989	0.97	3.98	0.08	0.26	5.26
1990	0.94	7.90	0.07	0.29	5.85
1991	0.45	6.15	0.02	0.27	5.28
1992	0.35	5.84	0.03	0.38	6.29
1993	0.67	5.81	0.06	0.20	6.73
1994	0.39	2.46	0.03	0.11	7.30

	ERC		R^2		ME of E_{t-1}
Year	**OLS1**	**LV1**	**OLS1**	**LV1**	**LV1**
1995	0.13	3.65	<0.01	0.23	7.88
1996	0.63	3.83	0.03	0.23	7.29
1997	0.80	2.77	0.04	0.13	8.02
1998	1.58	5.17	0.08	0.29	8.28
1999	0.62	6.28	0.01	0.16	7.69
2000	0.14	4.05	0.10	0.28	7.37
2001	0.49	1.82	0.05	0.23	7.74
2002	0.35	4.81	0.02	0.38	8.33
2003	0.09	2.24	0.09	0.20	8.05
2004	0.06	2.66	0.10	0.26	8.36
Mean	0.93	4.81	0.08	0.25	5.11
Median	1.84	5.18	0.09	0.25	4.78

Median of ERC_{LV1} - ERC_{OLS1}	**2.98*****
Median of R^2_{LV1} - R^2_{OLS1}	**0.16*****

Notes:
OLS1: OLS regression estimated with the previous earnings E_{t-1};
LV1: latent variable model estimated with the time-series forecast F_{TS} and the component forecast F_{CF};
ME of E_{t-1}: the variance of the measurement error in the previous earnings E_{t-1} as a proxy for the market's earnings expectations. It is calculated according to Equation A6 in Appendix A. The numbers are multiplied by 1000; and
One tailed test. *** significance <0.01; ** significance<0.05; *significance<0.10 .

Table 4

Time Trend of ERCs, R^2, and Measurement Error of Cross-sectional Estimations of Annual Data (1963 – 2004)

Panel A: Separate regressions of ERCs and R^2 on time indicator.

$$\mathbf{ERC_t = a_1 + a_2 * t + e_t ;}$$
$$\mathbf{R^2_t = a_1 + a_2 * t + e_t ;}$$

t = 0, 1, 2, . . . 41, indicating 1963 to 2004

Dependent Variable	**a_1**	**a_2**	**Adj R^2**
ERC_{OLS1}	4.442	-0.124	0.52
	[<0.01]	(<0.01)	
ERC_{LV1}	7.967	-0.071	0.04
	[<0.01]	(0.14)	
R^2_{OLS1}	0.145	-0.024	0.44
	[<0.01]	(<0.01)	
R^2_{LV1}	0.271	-0.008	0.03
	[<0.01]	(0.72)	

Panel B: Time regressions of ERCs and R^2

$$\mathbf{ERC_t = a_1 + a_2 * t + a_3 * D_i * t + e_t;}$$
$$\mathbf{R^2_t = a_1 + a_2 * t + a_3 * D_i * t + e_t;}$$

$t = 0, 1, 2, \ldots 41$, indicating 1963 to 2004;
$D_i = 1$ when using the latent viable model.

Dependent Variable	a_1	a_2	a_3	Adj R^2
ERC	0.944	-0.027	0.023	0.31
	[<0.01]	(<0.01)	(<0.01)	
R^2	0.686	-0.022	0.024	0.39
	[<0.01]	(<0.01)	(<0.01)	

Panel C: Time regressions of variance of measurement error (ME)

$\mathbf{ME_t = a_1 + a_2 * t + e_t;}$ $t = 0, 1, 2, \ldots 41$, indicating 1963 to 2004

	a_1	a_2	Adj R^2
ME	1.82	0.414	0.72
	[<0.01]	(<0.01)	

Notes:
ERC (R^2) of OLS model and the latent variable model are both scaled by the first observation of the respective series.
OLS1: OLS regression estimated with the previous earnings E_{t-1};
LV1: latent variable model estimated with the time-series forecast F_{TS} and the component forecast F_{CF};
ME: the variance of the measurement error in the previous earnings E_{t-1} as a proxy for the market's earnings expectations. It is estimated with LV1 and is calculated according to Equation A6 in Appendix A. The numbers of ME are multiplied by 1000.
p value for one-tailed test in parentheses; p value for two-tailed test in bracket.

Table 5

The Cross-sectional Annual Estimation of Variance of Measurement Error (ME), ERC, and R^2 with OLS and the Latent Variable Model (1984 - 2004)

	ERC				R^2				ME of E_{t-1}	ME of F_{AN}	Difference Between 2 MEs
Year	OLS1	OLS2	LV1	LV2	OLS1	OLS2	LV1	LV2	LV2	LV2	
1984	0.88	2.56	5.64	5.65	0.14	0.23	0.26	0.31	3.85	0.92	2.93
1985	1.92	2.19	8.88	6.45	0.14	0.17	0.25	0.31	4.20	0.98	3.22
1986	0.51	1.90	3.87	4.80	0.03	0.24	0.34	0.34	4.95	1.17	3.78
1987	0.67	1.39	2.91	4.00	0.06	0.19	0.21	0.33	5.01	0.99	4.02
1988	0.31	1.87	2.02	3.49	0.02	0.04	0.22	0.23	6.20	1.43	4.77
1989	0.97	2.77	3.98	4.79	0.08	0.22	0.26	0.26	5.01	1.63	3.38
1990	0.94	2.89	7.90	8.04	0.07	0.27	0.29	0.33	5.80	1.80	4.00
1991	0.45	0.98	6.15	6.07	0.02	0.11	0.27	0.31	5.14	1.86	3.28
1992	0.35	1.98	5.84	7.29	0.03	0.21	0.38	0.38	6.31	1.99	4.32
1993	0.67	0.77	5.81	5.93	0.06	0.06	0.20	0.21	6.45	1.68	4.77
1994	0.39	1.67	2.46	5.93	0.03	0.10	0.11	0.15	7.03	1.56	5.47
1995	0.13	1.72	3.65	5.33	<0.01	0.11	0.23	0.23	7.44	1.77	5.67
1996	0.63	2.35	3.83	5.36	0.03	0.14	0.23	0.23	7.23	2.03	5.20
1997	0.8	1.33	2.77	4.48	0.04	0.04	0.13	0.13	8.00	1.90	6.10
1998	1.58	3.50	5.17	5.68	0.08	0.17	0.29	0.30	7.55	2.11	5.44
1999	0.62	2.77	6.28	7.03	0.01	0.11	0.16	0.20	7.71	2.53	5.18
2000	0.13	2.32	4.05	4.49	0.10	0.09	0.28	0.32	7.39	2.32	5.07
2001	0.49	1.19	1.82	2.57	0.05	0.12	0.23	0.28	7.28	2.34	4.94
2002	0.35	0.98	4.81	4.46	0.02	0.03	0.38	0.35	7.98	2.17	5.81
2003	0.06	-0.07	2.24	2.67	0.03	<0.01	0.20	0.20	7.42	2.66	4.76
2004	0.09	2.10	2.66	4.03	0.05	0.11	0.26	0.26	7.54	2.24	5.30
Mean	0.70	1.87	4.42	5.17	0.05	0.13	0.25	0.27	6.45	1.81	4.64
Median	0.63	1.90	3.98	5.33	0.04	0.11	0.26	0.28	7.03	1.86	4.77

Notes:

OLS1: OLS regression estimated with the previous earnings E_{t-1};

OLS2: OLS regression estimated with the analyst forecast F_{AN};

LV1: latent variable model estimated with the time-series forecast F_{TS} and the component forecast F_{CF};

LV2: latent variable model estimated with the time-series forecast F_{TS} and the analyst forecast F_{AN};

ME of E_{t-1} (F_{AN}): the variance of the measurement error in the previous earnings E_{t-1} (analyst forecasts F_{AN}) as a proxy for the market's earnings expectations. It is estimated with LV2 and is calculated according to Equation A6 (A7) in Appendix A. The numbers are multiplied by 1000.

Table 6

Time Trend of ERCs, R^2, and Measurement Error of Cross-sectional Estimations of Annual Data (1984 – 2004)

Panel A: Time Regressions of ERCs and R^2

$$\mathbf{ERC_t = a_1 + a_2 * t + e_t ;}$$
$$\mathbf{R^2_t = a_1 + a_2 * t + e_t}$$

T = 0, 1, 2, . . . 20, indicating 1984 to 2004

	Dependent Variable	a_1	a_2	Adj R^2
OLS1	**ERC**	1.329	-0.382	0.17
		[<0.01]	(0.05)	
OLS2	**ERC**	3.177	-0.033	0.07
		[<0.01]	(0.14)	
LV2	**ERC**	6.514	-0.019	<0.01
		[<0.01]	(0.32)	
OLS1	**R^2**	1.273	-0.049	0.14
		[<0.01]	(0.04)	
OLS2	**R^2**	0.372	-0.013	0.08
		[<0.01]	(0.02)	
LV2	**R^2**	0.610	0.001	0.02
		[<0.01]	(0.37)	

Panel B: Time Regressions of ERCs and R^2

$$\mathbf{ERC_t = a_1 + a_2 * t + a_3 * DAN*t + a_4*DLV*t + e_t;}$$
$$\mathbf{R^2_t = a_1 + a_2 * t + a_3 * DAN*t + a_4*DLV*t + e_t;}$$

DAN = 1 when using OLS regression with analyst forecasts (OLS2);
DLV = 1 when using the latent variable model (LV2); and
t = 0, 1, 2, . . . 20, indicating 1984 to 2004.

Dependent Variable	a_1	a_2	a_3	a_4	Adj R^2
ERC	1.588	-0.042	-0.011	0.061	0.21
	[<0.01]	(0.03)	(0.72)	(<0.01)	
R^2	0.850	-0.053	0.019	0.034	0.35
	[<0.01]	(<0.01)	(0.09)	(<0.01)	

Panel C: Time regressions of variance of measurement error (ME)

$$\mathbf{ME_t = a_1 + a_2 *t + e_t;}\quad t = 0, 1, 2, . . . 20, \text{ indicating 1984 to 2004}$$

	a1	a2	R2
ME of E_{t-1}	4.168	0.324	0.58
	[<0.01]	(<0.01)	
ME of F_{AN}	0.394	0.213	0.49
	[0.02]	(<0.01)	

Notes:
OLS1: OLS regression estimated with the previous earnings E_{t-1};
OLS2: OLS regression estimated with analyst forecast F_{AN};
LV2: latent variable model estimated with the time-series forecast F_{TS} and analyst forecast F_{AN};
ME of E_{t-1}: the variance of the measurement error in the previous earnings E_{t-1} as a proxy for the market's earnings expectations. It is estimated with LV2 and is calculated according to Equation A6 in Appendix A. The number is multiplied by 1000;
ME of F_{AN}: the variance of the measurement error in analyst forecast F_{AN} as a proxy for the market's earnings expectations. It is estimated with LV2 and is calculated according to Equation A7 in Appendix A. The numbers are multiplied by 1000.
p value for one-tailed test in parentheses; p value for two-tailed test in bracket.

Table 7

Firm-specific Estimations of Annual Data

Panel A: Comparison of ERCs and R^2s over time

		ERC_{OLS1}	ERC_{LV1}	ERC_{LV1}-ERC_{OLS1}
	90%	8.64	17.11	12.40
Old	75%	4.88	7.24	3.53
Period	**50%**	**3.31**	**5.19**	1.21***
1963-1983	25%	1.01	1.13	-2.54
	10%	-6.52	-4.69	-11.02
	90%	3.88	17.01	14.97
New	75%	2.21	6.29	5.34
Period	**50%**	**0.79**	**2.32**	1.44***
1984-2004	25%	0.15	0.33	0.02
	10%	-0.65	-0.72	-1.03
Median Change:		**-1.94*** **	**-0.26**	**2.15*** **

		R^2_{OLS1}	R^2_{LV1}	R^2_{LV1}- R^2_{OLS1}
	90%	0.43	0.79	1.75
Old	75%	0.29	0.61	0.47
Period	**50%**	**0.14**	**0.28**	**0.03*** **
1963-1983	25%	0.04	0.09	-0.08
	10%	0.01	0.03	-0.23
	90%	0.32	0.77	1.62
New	75%	0.18	0.54	0.38
Period	**50%**	**0.07**	**0.23**	**0.07*** **
1984-2004	25%	0.02	0.09	-0.12
	10%	0.00	0.02	-0.29
Median Change:		**-0.04*** **	**-0.01**	**0.05*** **

Panel B:
The variances of measurement error (ME) in annual earnings changes of two periods

		ME of E_{t-1}
Old Period 1963-1983	90%	7.36
	75%	4.14
	50%	**2.31**
	25%	1.69
	10%	0.47
New Period 1984-2004	90%	9.04
	75%	7.90
	50%	**6.67**
	25%	3.51
	10%	2.41
Median Change:		**4.30*****

Panel C:
The variances of measurement error (ME) in annual earnings changes increases with R&D

$$\mathbf{ME = a_0 + a_1 * R\&D + e}\ ;$$

Dependent Variable	a_0	a_1	Adj R^2
ME	**8.33*****	**0.21****	**0.05**

Panel D:
The variances of measurement error (ME) in annual earnings changes are larger for loss firms

		ME
Old Period 1963-1983	**Loss Firms: 51**	**5.45**
	Profit Firms: 201	**1.91**
New Period 1984-2004	**Loss Firms: 161**	**9.38**
	Profit Firms: 91	**4.54**

Notes:
OLS1: OLS regression estimated with the previous earnings E_{t-1};
LV1: latent variable model estimated with the time-series forecast F_{TS} and the component forecast F_{CF};
ME of E_{t-1}: the variance of the measurement error in the previous earnings E_{t-1} as a proxy for the market's earnings expectations. It is estimated with LV1 and is calculated according to Equation A6 in Appendix A. The numbers are multiplied by 1000;
Loss Firms are defined as firms with more than two negative earnings of the 21 years period;
One tailed test. *** significance <0.01; ** significance<0.05; *significance<0.10

Table 8

The Association between ERC and ERC Determinants

$$\mathbf{ERC = a_0 + a_1 * Risk + a_2 * Growth + a_3 * Persistence + a_4 * Size + e_t}$$

Dependent Variable	a_0	a_1	a_2	a_3	a_4	Adj R^2
ERC_{OLS1}	44.35	-0.09	0.12	0.24	-0.15	0.09
	[<0.01]	(0.03)	(<0.01)	(<0.01)	(<0.01)	
ERC_{LV1}	48.77	-0.27	0.15	0.34	-0.21	0.27
	[<0.01]	(<0.01)	(<0.01)	(<0.01)	[<0.01]	

Notes:
ERC is estimated firm-specifically with annual data for period 1963-1983 and 1984-2004;
Risk: the market model systematic risk estimated by regressing monthly returns on the CRSP equally weighted return index;
Growth: the average assets growth rate;
Persistence: earnings persistence, defined as the OLS coefficient of regressing current earnings on last earnings;
Size: defined as total assets;
All the variables in the regressions are ranked from 0 to 100;
OLS1: OLS regression (firm-specific) estimated with the previous earnings E_{t-1};
LV1: latent variable model (firm-specific) estimated with the time-series forecast F_{TS} and the earnings component forecast F_{CF};
p value for one-tailed test in parentheses; p value for two-tailed test in bracket.

Table 9

The Cross-sectional Quarterly Estimation of Variance of Measurement Error (ME), ERC and R^2 with OLS and the Latent Variable Model (1984 – 2004)

		ERC			R2			ME	
Year	**Quarter**	**OLS1**	**OLS2**	**LV2**	**OLS1**	**OLS2**	**LV2**	E_{t-4}	F_{AN}
1984	**1**	-0.20	1.63	5.84	0.00	0.17	0.35	0.22	0.02
1984	**2**	-0.02	-0.20	-0.06	0.00	0.01	0.00	0.19	0.04
1984	**3**	1.54	6.04	13.49	0.09	0.07	0.64	0.01	0.06
1984	**4**	1.02	2.63	4.34	0.03	0.20	0.17	0.26	0.05
1985	**1**	0.46	2.85	3.80	0.03	0.19	0.16	0.01	0.06
1985	**2**	0.58	0.99	0.64	0.02	0.03	0.03	0.21	0.07
1985	**3**	1.38	5.08	8.78	0.07	0.39	0.33	0.25	0.09
1985	**4**	1.36	2.58	5.02	0.04	0.19	0.17	0.17	0.12
1986	**1**	0.01	0.96	0.19	0.00	0.01	0.00	0.12	0.08
1986	**2**	0.11	0.40	2.92	0.01	0.00	0.01	0.03	0.08
1986	**3**	1.15	4.78	3.17	0.03	0.02	0.03	0.34	0.07
1986	**4**	0.42	1.42	0.38	0.02	0.00	0.01	0.23	0.07
1987	**1**	0.04	1.34	6.65	0.01	0.15	0.14	0.05	0.11
1987	**2**	-0.31	-1.36	0.08	0.00	0.01	0.00	0.09	0.07
1987	**3**	1.27	4.14	2.77	0.03	0.03	0.03	0.10	0.06
1987	**4**	-0.24	3.72	10.62	0.01	0.43	0.36	0.27	0.05
1988	**1**	0.15	1.89	1.87	0.02	0.04	0.04	0.29	0.05
1988	**2**	0.02	-0.43	0.31	0.00	0.00	0.00	0.16	0.04
1988	**3**	0.45	3.34	3.81	0.00	0.08	0.07	0.29	0.04
1988	**4**	1.22	3.68	1.38	0.02	0.00	0.01	0.29	0.06
1989	**1**	1.09	2.34	1.71	0.08	0.06	0.06	0.38	0.06
1989	**2**	0.05	2.35	1.48	0.05	0.08	0.07	0.09	0.05
1989	**3**	0.16	3.65	0.45	0.01	0.01	0.00	0.01	0.07
1989	**4**	2.19	7.26	5.27	0.07	0.09	0.08	0.55	0.06
1990	**1**	0.08	2.18	1.53	0.01	0.00	0.02	0.24	0.12
1990	**2**	0.01	0.20	0.61	0.00	0.00	0.01	0.30	0.09
1990	**3**	0.83	5.04	7.74	0.01	0.30	0.26	1.03	0.08
1990	**4**	0.17	0.78	0.74	0.00	0.01	0.02	0.22	0.07
1991	**1**	0.22	0.88	1.50	0.02	0.02	0.03	0.18	0.08
1991	**2**	0.41	-0.19	0.08	0.04	0.01	0.00	0.14	0.09
1991	**3**	0.74	4.41	5.34	0.00	0.05	0.05	0.12	0.08
1991	**4**	0.20	7.69	12.46	0.03	0.14	0.37	0.32	0.07
1992	**1**	1.07	2.38	2.35	0.05	0.10	0.09	0.01	0.06
1992	**2**	0.15	1.53	1.33	0.04	0.07	0.06	0.35	0.06
1992	**3**	1.39	7.09	10.00	0.06	0.26	0.22	0.22	0.07

		ERC			R2			ME	
Year	**Quarter**	**OLS1**	**OLS2**	**LV2**	**OLS1**	**OLS2**	**LV2**	E_{t-4}	F_{AN}
1992	**4**	1.19	11.04	13.38	0.03	0.41	0.34	0.29	0.07
1993	**1**	0.76	3.71	2.63	0.06	0.05	0.05	0.08	0.08
1993	**2**	0.07	0.80	0.12	0.00	0.01	0.00	0.44	0.06
1993	**3**	1.18	5.55	7.76	0.02	0.18	0.16	0.29	0.07
1993	**4**	2.81	7.06	4.34	0.06	0.04	0.04	0.02	0.05
1994	**1**	0.98	4.36	0.07	0.02	0.01	0.00	0.08	0.05
1994	**2**	1.94	2.27	1.51	0.03	0.06	0.05	0.04	0.04
1994	**3**	0.03	3.36	0.38	0.00	0.01	0.00	0.09	0.05
1994	**4**	1.04	5.62	10.98	0.06	0.47	0.39	0.11	0.06
1995	**1**	1.21	5.41	5.93	0.06	0.26	0.23	0.19	0.08
1995	**2**	-0.09	-0.19	-0.41	0.00	0.00	0.00	0.12	0.06
1995	**3**	1.91	4.27	-1.74	0.02	0.00	0.01	0.17	0.07
1995	**4**	0.81	10.15	7.55	0.07	0.13	0.12	0.38	0.08
1996	**1**	0.54	3.61	4.78	0.03	0.08	0.07	0.32	0.07
1996	**2**	-0.55	-2.57	-2.39	0.00	0.05	0.05	0.29	0.07
1996	**3**	0.16	1.13	5.85	0.03	0.04	0.04	0.31	0.07
1996	**4**	0.12	1.17	1.45	0.00	0.00	0.01	0.19	0.07
1997	**1**	-1.27	5.91	6.47	0.03	0.12	0.11	0.18	0.07
1997	**2**	0.31	-0.03	0.17	0.00	0.01	0.00	0.48	0.08
1997	**3**	0.34	4.34	2.95	0.01	0.01	0.02	0.32	0.09
1997	**4**	1.42	7.62	5.79	0.02	0.07	0.08	0.29	0.14
1998	**1**	0.50	1.53	1.37	0.00	0.01	0.01	0.18	0.13
1998	**2**	-1.61	4.74	1.89	0.00	0.01	0.03	0.13	0.17
1998	**3**	0.00	2.16	-4.50	0.02	0.02	0.03	0.16	0.15
1998	**4**	-0.18	2.03	0.30	0.01	0.01	0.00	0.11	0.09
1999	**1**	1.62	8.49	2.48	0.02	0.02	0.01	0.27	0.18
1999	**2**	0.01	4.65	0.26	0.01	0.03	0.00	0.25	0.22
1999	**3**	2.14	12.21	21.65	0.02	0.35	0.31	0.21	0.21
1999	**4**	-0.68	2.20	-2.04	0.01	0.02	0.01	0.27	0.23
2000	**1**	1.19	6.36	2.69	0.02	0.00	0.03	0.15	0.19
2000	**2**	-0.55	-1.72	-0.29	0.00	0.02	0.00	0.12	0.14
2000	**3**	0.92	4.02	2.78	0.02	0.06	0.06	0.07	0.10
2000	**4**	0.49	2.05	1.34	0.01	0.04	0.05	0.20	0.14
2001	**1**	0.54	4.65	3.35	0.05	0.09	0.09	0.17	0.15
2001	**2**	-0.23	-0.47	0.39	0.00	0.01	0.00	0.09	0.10
2001	**3**	0.20	5.16	30.21	0.00	0.14	0.34	0.26	0.10
2001	**4**	0.23	2.63	6.66	0.01	0.13	0.12	0.31	0.10
2002	**1**	1.02	9.18	7.41	0.03	0.12	0.20	0.27	0.15
2002	**2**	0.09	0.38	0.84	0.00	0.06	0.05	0.21	0.08
2002	**3**	0.78	1.88	3.00	0.04	0.07	0.06	0.18	0.07
2002	**4**	0.42	1.96	0.84	0.00	0.01	0.02	0.27	0.08
2003	**1**	0.05	2.46	-0.14	0.03	0.01	0.00	0.49	0.07
2003	**2**	1.19	-0.94	-0.64	0.00	0.00	0.01	0.79	0.06

		ERC			R2			ME	
Year	**Quarter**	**OLS1**	**OLS2**	**LV2**	**OLS1**	**OLS2**	**LV2**	E_{t-4}	F_{AN}
2003	**3**	0.11	2.21	0.72	0.00	0.01	0.00	0.28	0.06
2003	**4**	0.33	6.00	5.64	0.00	0.12	0.20	0.72	0.06
2004	**1**	0.41	3.66	1.57	0.07	0.10	0.01	0.60	0.06
2004	**2**	1.10	0.13	0.77	0.00	0.11	0.11	0.21	0.11
2004	**3**	0.14	1.18	1.76	0.03	0.00	0.00	0.28	0.08
2004	**4**	0.29	4.29	0.79	0.00	0.02	0.02	0.18	0.08
	Mean	**0.53**	**3.27**	**3.54**	**0.02**	**0.08**	**0.09**	**0.23**	**0.09**
	Median	**0.41**	**2.63**	**1.82**	**0.02**	**0.04**	**0.04**	**0.21**	**0.07**
	Median of ERC_{LV2} - ERC_{OLS1}				**1.03*****				
	Median of R^2_{LV2} - R^2_{OLS1}				**0.02*****				
	Median of ERC_{LV2} - ERC_{OLS2}				**0.04**				
	Median of R^2_{LV2} - R^2_{OLS2}				**-0.01**				

Notes:
OLS1: OLS regression estimated with earnings of same quarter of the previous year: E_{t-4};
OLS2: OLS regression estimated with the analyst forecast F_{AN};
LV2: latent variable model estimated with the time-series forecast F_{TS} and the analyst forecasts F_{AN};
ME of E_{t-4} (analyst forecasts F_{AN}): the variance of the measurement error in E_{t-4} (analyst forecasts F_{AN}) as a proxy for the market's earnings expectations. It is calculated according to Equation A6 in Appendix A. The numbers are multiplied by 1000; and
One tailed test. *** significance <0.01; ** significance<0.05; *significance<0.10 .

Table 10

Time Trend of ERCs, R^2, and Measurement Error of Cross-sectional Quarterly Estimations (1984 – 2004)

Panel A: Separate regressions of ERCs and R^2 on time indicator.

$$\mathbf{ERC_t = a_1 + a_2 * t + e_t;}$$
$$\mathbf{R^2_t = a_1 + a_2 * t + e_t;}$$

t = 0, 1, 2, . . . 83, indicating first quarter of 1984 to the fourth quarter of 2004

Dependent Variable	a_1	a_2	Adj R^2
ERC_{OLS1}	0.6583	-0.0034	0.011
	[<0.01]	(0.35)	
ERC_{OLS2}	0.1143	-0.0069	0.023
	[<0.01]	(0.16)	
ERC_{LV2}	3.9576	-0.0102	0.002
	[<0.01]	(0.67)	
R^2_{OLS1}	0.0289	-0.0003	0.032
	[<0.01]	(0.11)	
R^2_{OLS2}	2.6042	-0.0155	0.016
	[<0.01]	(0.26)	
R^2_{LV2}	0.1353	-0.0009	0.052
	[<0.01]	(0.13)	

Panel B: Time regressions of variance of measurement error (ME)

$\mathbf{ME_t = a_1 + a_2 * t + e_t}$; t = 0, 1, 2, . . . 83, indicating first quarter of 1984 to the fourth quarter of 2004

	$\mathbf{a_1}$	$\mathbf{a_2}$	**Adj R^2**
ME of E_{t-4}	0. 190	0.005	0.01
	[<0.01]	(0.15)	
ME of F_{AN}	0. 055	0.007	0.17
	[<0.01]	(<0.01)	

Notes:
OLS1: OLS regression estimated with earnings of same quarter of the previous year: E_{t-4};
OLS2: OLS regression estimated with the analyst forecast F_{AN};
LV2: latent variable model estimated with the time-series forecast F_{TS} and the analyst forecasts F_{AN};
ME of E_{t-4} (analyst forecasts F_{AN}): the variance of the measurement error in E_{t-4} (analyst forecasts F_{AN}) as a proxy for the market's earnings expectations. It is calculated according to Equation A6 in Appendix A. The numbers are multiplied by 1000; and
p value for one-tailed test in parentheses; p value for two-tailed test in bracket.

Table 11

Firm-specific Estimations of Quarterly Data

Panel A: Comparison of ERCs and R^2s over time

		ERC_{OLS1}	ERC_{OLS2}	ERC_{LV2}
	90%	6.661	7.925	25.646
Old	75%	2.950	3.760	7.143
Period	**50%**	**1.077**	**1.480**	**2.231**
1984-1994	25%	0.147	0.154	0.182
	10%	-0.353	-0.873	-0.919
	90%	3.192	5.052	12.980
New	75%	1.409	2.227	3.811
Period	**50%**	**0.614**	**1.009**	**1.119**
1994-2004	25%	0.125	0.131	0.245
	10%	-1.611	-1.137	-3.790
Median of Changes:		**-0.294**	**-0.255**	**-0.262**

		R^2_{OLS1}	R^2_{OLS2}	R^2_{LV1}
	90%	0.131	0.323	0.413
Old	75%	0.078	0.194	0.187
Period	**50%**	**0.043**	**0.085**	**0.124**
1984-1994	25%	0.029	0.033	0.042
	10%	0.001	0.003	0.005
	90%	0.119	0.290	0.400
New	75%	0.083	0.181	0.182
Period	**50%**	**0.028**	**0.092**	**0.111**
1994-2004	25%	0.025	0.016	0.033
	10%	0.001	0.002	0.006
Median of Changes:		**-0.010**	**-0.014**	**-0.006**

Panel B:
The variances of measurement error (ME) of two periods

		ME of E_{t-4}	**ME of F_{AN}**
	90%	0.546	0.214
	75%	0.337	0.121
Old Period 1984-1994	**50%**	**0.214**	**0.053**
	25%	0.147	0.029
	10%	0.022	0.013
	90%	0.775	0.409
	75%	0.392	0.164
New Period 1994-2004	**50%**	**0.254**	**0.077**
	25%	0.186	0.053
	10%	0.023	0.011
Median of Changes:		**-0.032**	**-0.028****

Notes:
OLS1: OLS regression estimated with earnings of same quarter of the previous year: E_{t-4};
OLS2: OLS regression estimated with the analyst forecast F_{AN};
LV2: latent variable model estimated with the time-series forecast F_{TS} and the analyst forecasts F_{AN};
ME of E_{t-4} (analyst forecasts F_{AN}): the variance of the measurement error in E_{t-4} (analyst forecasts F_{AN}) as a proxy for the market's earnings expectations. It is calculated according to Equation A6 in Appendix A. The numbers are multiplied by 1000; and
One tailed test. *** significance <0.01; ** significance<0.05; *significance<0.10 .

Appendix C: Models

Model 1: The Latent Variable Model

The variance-covariance matrix of the latent variable model is a four-by-four matrix as Equation A1:

$$\sum = \begin{pmatrix} VAR(RET) & COV(RET,E) & COV(RET,E-F_1) & COV(RET,E-F_2) \\ - & VAR(E) & COV(E,E-F_1) & COV(E,E-F_2) \\ - & - & VAR(E-F_1) & COV(E-F_1,E-F_2) \\ - & - & - & VAR(E-F_2) \end{pmatrix} \tag{A1}$$

The matrix in Equation A1 is composed of observable variance covariance information of the four variables (RET, E, $E-F_1$, and $E-F_2$). By the definition of Equations 3 to 6, the matrix contains the following ten covariance equations, which are composed of eight unknown variables: β, b_1, b_2, $VAR(\varepsilon_1)$, $VAR(\varepsilon_2)$, $VAR(e)$, $VAR(F^*)$, and $VAR(UE)$.

$$\begin{cases} VAR(RET) = \beta^2 VAR(UE) + VAR(e) \\ VAR(E) = VAR(UE) + VAR(F^*) \\ VAR(E-F_1) = VAR(UE) + (1-b_1)^2 VAR(F^*) + VAR(\varepsilon_1) \\ VAR(E-F_2) = VAR(UE) + (1-b_2)^2 VAR(F^*) + VAR(\varepsilon_2) \\ COV(RET,E) = \beta VAR(UE) \\ COV(RET,E-F_1) = \beta VAR(UE) \\ COV(E,E-F_1) = VAR(UE) + (1-b_1)^2 VAR(F^*) \\ COV(RET,E-F_2) = \beta VAR(UE) \\ COV(E,E-F_2) = VAR(UE) + (1-b_2)^2 VAR(F^*) \\ COV(E-F_1,E-F_2) = VAR(UE) + (1-b_1)(1-b_2) VAR(F^*) \end{cases} \tag{A2}$$

The covariance equation system is identified and the expression of ERC is as follows:

$$\hat{\beta} = \frac{COV(RET,E)}{VAR(E) - COV(E,F_1)COV(E,F_2)/COV(F_1,F_2)} \tag{A3}$$

R^2, the explanatory power of unexpected earnings UE on stock returns RET, can be calculated as follows:

$$\begin{aligned} \hat{R}^2 &= \frac{\beta^2 VAR(UE)}{VAR(RET)} \\ &= \frac{COV(RET,E)^2}{(VAR(E) - COV(E,F_1)COV(E,F_2)/COV(F_1,F_2))VAR(RET)} \end{aligned} \tag{A4}$$

The latent variable model also provides a direct measure of the proxy errors in using previous earnings as a proxy for the market's earnings expectation F^*. As with Equations 4 and 5, suppose the previous period's earnings E_{t-1} is a proxy for the market's expectation F^* of current earnings E_t:

$$E_{t-1} = a_3 + b_3 F^* + \varepsilon_3 \tag{A5}$$

Then measurement error in using previous earnings as a proxy for the market's earnings expectation F^* is $-a_3 + (1-b_3)F^* - \varepsilon_3$. Its variance is as follows:

$$\frac{COV(E_t,F_1)COV(E_t,F_2)}{COV(F_1,F_2)} - 2COV(E_t,E_{t-1}) + VAR(E_{t-1}) \tag{A6}$$

The measurement error in F_1 is $-a_1 + (1-b_1)F^* - \varepsilon_1$. Its variance is as follows:

$$\begin{aligned} &\frac{(COV(E,F_2) - COV(F_1,F_2))^2 COV(E,F_1)}{COV(F_1,F_2)COV(E,F_2)} + VAR(E) \\ &- \frac{COV(E,F_1)COV(F_1,F_2)}{COV(E,F_2)} \end{aligned} \tag{A7}$$

And the variance of measurement error in F_2 can be calculated similar to Equation A7.

Model 2: The Time-Series Earnings Forecast Model (F_{TS})

In the latent variable model of this paper, following an efficient market theory, I assume that the time-series forecast F_{TS} is fully incorporated into stock prices before the return window of the model. To satisfy this assumption, the time-series forecast F_{TS} should be composed of information that is available to investors before the return window. Accordingly, F_{TS} should be an *ex ante* forecast (out-of-sample forecast) instead of an *ex post* forecast (within-sample forecast). Because of the limitations in the data availability of annual earnings, however, I cannot make an out-of-sample time-series forecast for annual earnings for the whole period. Therefore, I use a within-sample forecast for the period 1963 to 2004 in the main tests. In the sensitivity tests, out-of-sample time-series forecasts are conducted for the period from 1984 to 2004.

Because of the changes in time-series properties of earnings over time (e.g., Mao and McKeown (2005)), for each firm, I estimate the time-series forecast F_{TS} separately for the periods 1963 to 1983 and 1984 to 2004. The model for F_{TS} is decided by comparing the within sample residual standard errors (RSE) of the following models: RW, RW with drift, AR (1), AR (1) with first differences, AR (2), and AR (2) with first differences. I use the one with the smallest RSE to estimate F_{TS}. This model set is used because the estimation of these models requires fewer observations than other complicated ARIMA models.

Model 3: The Component Forecast Model (F_{CF})

Texts on financial statement analysis (e.g., Haskins et al. (1993, pp. 642-649), Schilit (1993, pp. 123-130), Stickney (1993, p. 102), White et al. (1994, pp. 138-159), and Kieso and Weygrandt (1995, p. 1231)) typically suggest examining a model incorporating the accrual and cash flow components of current earnings to predict future earnings. Sloan (1996) uses an component forecast model based on the accrual and cash flow components to examine the implications of these two components of current earnings to future earnings.

Based on these studies, I construct a component forecast model by regressing earnings E_t of period t on accrual, cash flow, and non-operating earnings NOE of period t-1:

$$E_t = \alpha_0 + \alpha_1 * Accrual_{t-1} + \alpha_2 * CashFlow_{t-1} + \alpha_3 * NOE_{t-1} + \gamma \quad \text{(A8)}$$

Earnings E_t are earnings before extraordinary items (EPS of Compustat item 58 multiplied by the number of common shares of Compustat item 54). Following Sloan (1996), accrual is defined as

$$Accrual = (\Delta CA - \Delta Cash) - (\Delta CL - \Delta DCL - \Delta TP) - Dep \quad \text{(A9)}$$

where ΔCA = change in current assets (Compustat item 4),

$\Delta Cash$ = change in cash and cash equivalents (Compustat item 1),

ΔCL = change in current liabilities (Compustat item 5),

ΔDCL = change in debt included in current liabilities (Compustat item 34) ,

ΔTP = per share change in income taxes payable (Compustat item 71), and

Dep = depreciation and amortization expenses (Compustat item 14).

Cash flow is measured as the difference between operating income (Compustat item 178) and the accrual component. Non-operating earnings NOE is defined as the difference between earnings before extraordinary items E_t and operating income (Compustat item 178). NOE is used because earnings E_t also includes part of the non-operating income, which is not included in either the accrual or the cash flow component of operating income. Earnings before extraordinary items E_t have to be used in this paper for two reasons: first, it is consistent with the earnings definition in previous studies of time trend of the value relevance of earnings; and second, analyst forecasts are used in this paper, and analysts generally forecast earnings before extraordinary items.

Cross-sectional regressions are conducted for each year and for each industry S. The component forecast for earnings E_{t+1} of period t+1 is calculated as

$$F_{CF} = \hat{\alpha}_0 + \hat{\alpha}_1 * Accrual_t + \hat{\alpha}_2 * CashFlow_t + \hat{\alpha}_3 * NOE_t \qquad \text{(A10)}$$

where $\hat{\alpha}_0$ to $\hat{\alpha}_3$ are the estimated OLS coefficients from Equation A8.

CHUNLIN MAO

EDUCATION

Ph.D. in Accounting, August 2006
Pennsylvania State University—University Park, PA

Study in Ph.D. program in Accounting, August-December 2000
Baruch College, City University of New York—New York, NY

B.A. in Accounting, July 1996
Peking University—Beijing, P.R. China

DISSERTATION

"Is the Value Relevance of Earnings Information Really Decreasing Over Time?" Dissertation Committee: Orie E. Barron, James C. McKeown (Chair), Karl A. Muller and Arun Upneja (Department of Hospitality Management, Penn State University)

WORKING PAPER AND WORK IN PROGRESS

"Does Random Walk Still Rule Annual Accounting Earnings?" (with James C. McKeown)

"Does Regulation FD Benefit Investors? New Evidence from a Latent Variable Model" (with James C. McKeown) (in progress)

INVITED PRESENTATION

Discussant for the Value Relevance Session, AAA, San Francisco, 2005
University of Georgia, 2006
George Washington University, 2006
The Chinese University of Hong Kong, 2006
The University of Hong Kong, 2006
Nanyang Business School, 2006
Singapore Management University, 2006
The National University of Singapore, 2006

PROFESSIONAL EXPERIENCE

Ad hoc reviewer, Financial Accounting and Reporting Section (FARS) Conference, 2004

Major Instructor for *Financial and Managerial Accounting for Decision Making*, Summers of 2003-2005. Pennsylvania State University.

AWARDS

G. Kenneth Nelson Fellowship, 2002-2006
W. Edward and Kay M. Hastings Graduate Scholarship, 2003