The Dissertation Committee for Brian Michael Bratten Certifies that this is the approved version of the following dissertation:

Analysts' use of earnings components in predicting future earnings

Committee:

Ross Jennings, Supervisor

Keith Brown

Michael Clement

Robert Freeman

Thomas Sager

Yanfeng Xue

Analysts' use of earnings components in predicting future earnings

by

Brian Michael Bratten, B.B.A., M.S.

Dissertation

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Doctor of Philosophy

The University of Texas at Austin

August 2009

Dedication

To Kristy.

Acknowledgements

I am sincerely grateful for the many insightful comments from my committee members: Keith Brown, Michael Clement, Robert Freeman, Ross Jennings (chair), Thomas Sager, and Yanfeng Xue. I am most especially thankful for Ross's guidance on this project and others I have undertaken during the PhD program.

My dissertation has also benefited greatly from Department of Accounting faculty and doctoral student participants at both a brown bag and a research workshop at the University of Texas. Without the excellent training from the faculty members and vital support of the student colleagues, this project would not have been completed. Notably, Margaret Christ, Michael Crawley, and Casey Schwab have been tremendously helpful and supportive colleagues. I also acknowledge the financial support of the McCombs School of Business and the Graduate School at the University of Texas at Austin.

Most importantly, I thank my wife Kristy, my most treasured blessing, for encouraging me and providing comfort and happiness to our family during my PhD program and especially through the completion of this dissertation.

Analysts' use of earnings components in predicting future earnings

Publication No._____________

Brian Michael Bratten, Ph.D.

The University of Texas at Austin, 2009

Supervisor: Ross G. Jennings

This dissertation examines the general research issue of whether the components of earnings are informative and specifically 1) how analysts consider earnings components when predicting future earnings and 2) whether the information content in, and analysts' use of, earnings components have changed through time. Although earnings components have predictive value for future earnings based on each component's persistence, extant research provides only a limited understanding of whether and how analysts consider this when forecasting.

Using an integrated income statement and balance sheet framework to estimate the persistence of earnings components, I first establish that disaggregation based on the earnings components framework in this study is helpful to predict future earnings and helps explains contemporaneous returns. I then find evidence suggesting that although analysts consider the persistence of various earnings components, they do not fully integrate this information into their forecasts. Interestingly, analysts appear to be

selective in their incorporation of the information in earnings components, seeming to ignore information from components indicating lower persistence, which results in higher forecast errors. Conversely, when a firm's income is concentrated in high persistence items, analysts appear to incorporate the information into their forecasts, reducing their forecast errors.

I also report that the usefulness of components relative to aggregate earnings has dramatically and continuously increased over the past several decades, and contemporaneous returns appear to be much better explained by earnings components than aggregate earnings (than historically). Finally, the relation between analyst forecast errors and the differential persistence of earnings components has also declined over time, indicating that analysts appear to recognize the increasing importance of earnings components through time.

Table of Contents

List of Figures and Tables

Chapter 1. Introduction

This study examines how analysts consider the components of earnings when predicting future earnings and whether the information content in earnings components (above the information in earnings itself) and analysts' use of this information has changed through time. With the exception of the accrual anomaly research stream, only a small subset of accounting studies has examined the predictive ability of disaggregated earnings components for future earnings. In general, these papers find that a decomposition of earnings better predicts future earnings (e.g., Fairfield et al. 1996; Richardson et al. 2005). I extend this research stream by studying 1) whether analyst forecast revisions are related to relevant incremental information contained in earnings components, and 2) whether the importance of earnings components (relative to aggregate earnings) for predicting earnings has changed in recent years and how this relates to analysts' use of disaggregated information.

Disaggregated earnings components will have greater predictive ability for future earnings to the extent they have differential persistence. Analysts' use of this information is important because prior research suggests that this information is useful for explaining investors' response to current earnings and for predicting future earnings (Lipe 1986; Fairfield et al. 1996). Additionally, to the extent the differential persistence of earnings components is misunderstood by investors (i.e., Sloan 1996; Richardson et al. 2005), this study seeks evidence on whether analysts contribute to this type of apparent informational inefficiency (by making predictions consistent with the mispricing) or whether the market is unaided by analysts' correct interpretations. Because analysts play an important role in analyzing financial statements and disseminating this information to investors, analysts are unlikely to completely ignore the information provided by earnings components. However, due to information processing costs and the possibility of a myopic focus on aggregate net income or other signals, analysts also may not fully incorporate the differential persistence of these components when making future earnings forecasts, especially when considering constraints they face when processing complex (vs. simple) types of information (Plumlee 2003).

As a framework for my empirical analyses, I integrate two taxonomies—1) income statement items and 2) balance sheet "accrual" components—for classifying components of earnings. In this framework, I estimate the association between each earnings component and future earnings. I allow the associations between these components and future earnings to vary through time and I retain for my subsequent empirical tests the estimated levels of persistence of each component. With this data, I expect to find that contemporaneous returns and future earnings are better explained by the components of earnings than the aggregate earnings measure. This prediction is based on the empirical fact that when earnings components with differential persistence are aggregated, information is lost. Relative to aggregate earnings, earnings components will be most informative for firms which have differential persistence based on the composition of their components and the related persistence levels of each component. In other words, this will matter most when the components indicate a future earnings path different than aggregate earnings.[1] I improve upon prior studies by integrating earnings components taxonomies previously considered separately and by allowing the relations between the components and future earnings to vary through time. More importantly, the preliminary analyses I perform when developing my earnings component framework serve as a foundation for my examination of analysts' use of components in forecasting future earnings.

My primary analyses test the extent to which analysts utilize predictable earnings persistence (based on an analysis of earnings components) into their forecasts of future earnings by determining whether forecasts and forecast revisions are *related to* the persistence of these components. I find that forecasts and revisions are partially explained by the components. I then turn to an examination of whether the information is *fully* impounded, and consider analysts' forecast errors. Analysts' forecast errors are positively related to the extent of differential information between earnings components and aggregate earnings. Further, improvement from the earnings component model is positively associated with their errors, suggesting that analysts' incorporation of the persistence of earnings components may be incomplete. Interestingly, analysts seem to ignore (incorporate) information from components when this information indicates lower (higher) persistence of earnings, which results in higher (lower) forecast errors. In other words, analysts appear to selectively incorporate information from earnings components, and forecast errors are greatest for firms whose income is concentrated in components of low persistence.

[1] In cases where the persistence differs and investors accordingly value them differently, the coefficients on the earnings components will differ when regressing returns on the components (Jennings 1990).

Finally, I investigate how the informativeness of earnings components has changed over time. Prior research has documented a decline in both the value relevance and the persistence of earnings over the past few decades (Collins et al. 1997; Francis and Schipper 1999; Gu 2007; Dichev and Tang 2008). Standard setters have moved to a balance sheet approach with an emphasis on the fair values of balance sheet accounts rather than an income statement approach which followed principles of historical cost and matching (e.g., FASB 1993, 1998, 2001, 2006). Thus, an open question is whether information from the components compensates for the apparent loss of information from earnings. I examine whether earnings components are more useful relative to aggregate earnings in recent years compared to earlier time periods.

Further, previous studies investigating the time series properties of earnings components have generally assumed that the information content of these components has remained constant over time and examined coefficients on the cross-sectional components when examining the predictability of future earnings or discussing the earnings/return relation.[2] To the extent that the information provided by earnings components (or market participants' use of the information provided by earnings components) has increased, earnings components may better explain future earnings or contemporaneous returns through time.

[2] There are some exceptions to this. For example, Fairfield et al. (1996) utilized a similar methodology as the implementation in my preliminary analyses to "roll" the predictive ability of components through time, and Collins and Kothari (1989) introduces the interest rate as a time-varying factor influencing the relation between aggregate earnings and the earnings response coefficient. However, these studies do not investigate the manner in which the components change over time nor whether they are more or less useful to include in association or predictive tests relative to aggregate earnings.

My analyses of the change in the informativeness of earnings components begin with an analysis of the change through time of the out-of-sample forecasting accuracy of the earnings components model introduced earlier in my study. Results indicate that earnings components are in fact less predictive of future earnings for fiscal years ending between 1986 to 2007, relative to fiscal years ending between 1970 and 1985. However, this decrease in predictability of future earnings using components is much less substantial than the decrease in predictability of earnings based on using an aggregate earnings model. This suggests that the consideration of earnings components is now more important when predicting future earnings.

Supporting this interpretation, I find that in the post-1985 period (but not the pre-1986 period), the relation between contemporaneous returns and earnings surprises is much stronger when an earnings surprise is calculated by using earnings components and their various persistence levels as a benchmark, rather than when an earnings surprise is calculated by using an aggregate earnings as a benchmark. This indicates that investors appear to use earnings components as an expectation for earnings to a greater degree now than historically.

I also find a similar pattern for earnings predictability in the time period of the analyst forecast sample, and further report that analysts appear to realize this pattern. That is, earnings components are less predictive of future earnings for fiscal years ending between 2001 to 2007, relative to years ending between 1994 and 2000, but they are more predictive relative to aggregate earnings (because the predictability of the aggregate earnings model deteriorated during this time period). Examining analysts' forecasts of future earnings in these same two periods, I find that analysts' forecast errors are less associated with differential information from the components in the later period, consistent with analysts' recognition of the relative improvement in the predictiablity of earnings using information from the components.

This study is timely as standard setters are working toward a financial statement presentation standard that will "address the presentation and display of financial statement information, including the classification and display of line items and the aggregation of line items into subtotals and totals" (FASB and IASB 2008). Standard setters have tentatively "decided to focus on disaggregating comprehensive income according to the characteristics of *persistence* and *subjectivity*" (FASB 2008, emphasis in the original). Accordingly, they may be informed by my analysis about the differential persistence and usefulness of various earnings components, the extent to which they are incorporated by financial statement users such as analysts when predicting future earnings, and the change in the relative usefulness of components as accounting standards have evolved.

In the next chapter, I discuss the literature upon which I build my analyses. In chapter 3 I outline the research areas addressed in this study. Chapter 4 details the general research design and construction of key variables. I document results of my preliminary analyses about the informativeness of earnings components in chapter 5. In chapter 6, I present the empirical tests and results for the primary analyses investigating analysts use of earnings components, and in chapter 7 I discuss my supplemental analyses which examine the change in the information content of earnings components and analysts' use of this information through time. Chapter 8 concludes.

Chapter 2. Prior literature

2.A. Earnings components

The assumption that earnings components are incrementally informative to the process of making predictions about future earnings follows from both theoretical and empirical accounting literature. Ohlson (1999) illustrates how "transitory" earnings components are not relevant to forecasts of the aggregate earnings of the next period. Across fourteen industries, Barth et al. (1999) extend this framework to include components (cash flows and accruals) that are neither fully permanent nor transitory. They empirically show that the higher (lower) the proportion of current earnings is attributable to cash flows (accruals), the higher (lower) future abnormal earnings. Further, they show that disaggregating earnings into these components is relevant for forecasting future earnings.

Previous literature has also examined whether disaggregation of earnings better explains the magnitude of market participants' aggregate response to earnings or the expectation of firms' future earnings. In many early studies through the mid-1980s, the relation between unexpected earnings and returns, called the earnings response coefficient (ERC), was implicitly assumed by researchers to be the same across firms and across components of earnings.

Unlike earlier studies, Lipe (1986) does not focus on firms' aggregate earnings but instead decomposes its earnings into six separate components (gross profit, general and administrative expenses, depreciation expense, interest expense, income tax, and other items), examining the relation between these components and stock returns. He was motivated by the notion that the components of earnings may have differing levels of persistence and may thus be impounded into price differently.[3] He finds that unexpected returns are better explained by disaggregating the unexpected component shocks for the majority of firms. Lipe also shows that the extent to which the unexpected return is responsive to each component's earnings shock is related to his measure of persistence, although this relation is only marginally significant. Together, these results imply that different components of earnings have different implications for future earnings, and we may better predict future earnings and returns by better understanding the differential persistence of earnings components.

Ramakrishnan and Thomas (1998) suggest that earnings can be decomposed into three components—permanent, transitory, and price-irrelevant. They then develop a valuation model which incorporates these three components into returns separately, showing that the ERC is an average response to the unexpected portion of the each component. However, the authors' empirical analysis shows improvement to ERCs by adjusting for the statistical properties of earnings (autocorrelations) rather than directly decomposing earnings into permanent, transitory, and price-irrelevant components. Easton's (1998) discussion of Ramakrishnan and Thomas criticizes this aspect and suggests that researchers should study the role of variables other than earnings when

[3] Lipe defines persistence as present value of future earnings revisions "induced by the component shock," and measures persistence as the component shock's theoretical impact on the value of the firm based on the time-series properties of earnings. Elsewhere in this study I mean for persistence to refer to the extent to which earnings or an earnings component will translate into earnings in future periods. This meaning is consistent with other recent research (such as the accruals literature). In this literature, future earnings is regressed on past earnings or disaggregated earnings components and the differential coefficients on these components are interpreted as relative persistence levels (in-sample). Importantly, in this paper persistence differs from the concept of "predictability," which refers to the ability of the forecasting models to most closely predict future earnings (out-of-sample).

analyzing how the securities markets incorporate financial statement data other than earnings into returns.

Other studies examine the usefulness of various earnings components for forecasting future earnings. Fairfied et al. (1996) examine the predictability of future earnings based on using information contained in the components of earnings. In their study, disaggregating earnings into operating earnings, non-operating earnings and taxes, and special items and recognizing the cross-sectional persistence of these various items increased the predictability of one-year-ahead forecasts of ROE; further disaggregation was not beneficial in their study because of additional measurement error. Another interesting insight from their study is that while non-recurring items such as extraordinary items and discontinued items can be ignored when forecasting future earnings, special items have a non-zero level of recurrence and should be considered.

More narrowly, Fairfield and Yohn (2001) investigate whether the disaggregated components of return on net operating assets (RNOA)—asset turnover and profit margin—can better predict future changes in profitability than an aggregate measure. Using a sample of firms with positive profit margins, they show that the disaggregated RNOA measure is not incrementally useful at the next period's change in RNOA. Interestingly, however, they find that disaggregating the contemporaneous change in RNOA is useful in predicting future changes in RNOA. Specifically, the change in asset turnover is positively related to the future change in RNOA, while the change in profit margin is insignificant. The authors claim that the insignificant results for the change in profit margin may be the result of changes in accounting conservatism (economically less relevant than asset utilization) or earnings management. Another plausible alternative is that changes in asset turnover are more permanent than changes in profit margins due to competitive pressures in the market.

Richardson et al. (2005) disaggregate the accruals component of earnings into several categories that they rate as more or less reliable. This categorization depends on whether the measurement of the underlying assets for each accrual is "reliable" based on the definition of reliability found in Statement of Financial Accounting Concepts No. 2 (FASB 1980). The authors show that the persistence of earnings is lower for the accrual component of earnings than the cash component, and further, that among the various accruals, the persistence is lower for those that are associated with assets which have relatively less measurement reliability. Stock return results in their study suggest that investors fail to fully process information about earnings persistence that can be inferred based on the reliability of these accruals. The authors warn standard setters to be cautious about requiring relevant but less reliable information to be incorporated into earnings (such as the capitalization and amortization of research and development expenses).

In additional to studies of earnings persistence, other studies investigate the predictability of cash flows and earnings relative to cash flows. Barth et al. (2001) investigate the predictability of cash flows rather than earnings using components of accruals. The authors find that future cash flows can be better predicted using a disaggregation of accruals than using aggregate earnings or other predictors. Yet another study suggests that earnings persistence is influenced by the *sign* of accruals, and that earnings persistence relative to cash flows is improved by accruals for high accrual firms but reduced by accruals for low accrual firms (Dechow and Ge 2006).

In summary, prior literature about earnings components suggests the following: the earnings/returns relation is increasing in the perceived persistence of earnings, components of earnings have differential persistence, a decomposition of earnings can better predict future earnings, and investors fail to incorporate all of this information into price. I confirm some of these findings by investigating whether a mechanical forecasting model that incorporates the differential persistence of various earnings components can better predict future earnings, and then extend this line of research by examining whether analysts appear to consider the differential persistence of earnings components in their analyses.

In addition to analyzing analysts' use of earnings components, I anticipate that my analysis will incrementally contribute to the above and related literature because I include a more comprehensive set of earnings components than previously examined. I suggest two reasons that a more comprehensive disaggregation will result in greater predictability. First, integrating a decomposition based on income statement classifications with an accrual-based decomposition may result in more useful estimates of future earnings, relative to the separate analyses of the income statement components of operating earnings performed by Fairfield et al. (1996) and the accrual components by Richardson et al. (2005). Second, it may be more informative to separately evaluate the persistence of revenues and cost of goods sold (rather than considering the summary measure, gross margin). These are discussed in more detail in the next chapter.

Although there is an element of financial statement analysis and forecasting above, the research questions in this study (discussed in more detail in the next chapter) focus on the persistence of various earnings components for predicting earnings and explaining the behavior of market participants. These questions and this line of research differs from fundamental analysis research, which uses signals derived from financial statements and other disclosures to predict future returns or positive earnings shocks (Ou and Penman 1989; Lev and Thiagarajan 1993; Abarbanell and Bushee 1997; Abarbanell and Bushee 1998).

2.B. ANALYSTS USE OF EARNINGS COMPONENTS

This study provides evidence about analysts' use of earnings components in their forecasting process. Few prior studies in the accounting literature have attempted to examine this general research issue. Ali et al. (1992) provide some indirect evidence on this topic by examining the extent to which analysts are able to recognize the time-series properties of earnings. Rather than decomposing earnings into various components, Ali et al. (1992) use the earnings to price ratio (E/P) to proxy for the extent to which firms' earnings are transitory (have transitory components) and find that forecast errors are lower when E/P is high. They interpret this evidence as consistent with analysts differentiating partially between earnings components with permanent versus transitory components.

Mest and Plummer (1999) also take an indirect approach to investigate analysts' use of transitory earnings components. Research preceding their study identified a non-linear relation between abnormal returns and analyst forecast errors (e.g., Freeman and

Tse 1992). Mest and Plummer (1999) use the extent of non-linearity in the relation between returns and forecast revisions as a proxy for the extent of transitory earnings components. They find a more linear relation between returns and revisions of long-term forecasts (compared to short term forecasts) and conclude that analysts use transitory earnings components less in long-term forecasts.

Recently, researchers have begun to incorporate individual earnings components *directly* in studies involving analysts. Gu and Chen (2004) show that items excluded from analysts' forecasts have less persistence, lower future valuation multiples, and a lower correlation with future returns than included items. These results indicates that analysts are excluding the less useful or value relevant components, which may help investors in identifying what is and isn't relevant or likely to recur within aggregate GAAP earnings. However, Gu and Chen (2004) do not discuss how exclusions are used by analysts in making future forecasts. Analysts could ignore these items altogether or they could consider how different components map into future earnings based on different levels of persistence.

Bradshaw, Richardson, and Sloan (2001) report that analysts' forecast errors are greater for high-accrual firms, providing some evidence that the persistence of earnings components are not fully considered. However, the authors do not control for information known to be correlated with accruals—such as growth—which is also likely to be highly correlated with forecast error. This omission from the analysis suggests it would be an overstatement to claim that analysts completely ignore information in accruals. I complement evidence from prior research with a more complete and systematic analysis of the relation between the persistence of earnings components and analysts' earnings forecasts.

Concurrent work also investigates analysts' consideration of earnings components, although in a slightly different manner. For example, Ertimur, Mayew, and Stubben (2008) investigate the reputational effects of analysts' forecasts *of* disaggregated earnings line items such as sales. Interestingly, they find that non-reputable analysts are more likely to disaggregate earnings forecasts (consistent with incentives to signal ability). More relevant to my study, they report that analysts issuing sales forecasts are on average more accurate than those issuing only earnings forecasts. This may suggest that the analysts who consider these specific components more carefully (and report their component forecasts to I/B/E/S) are better able to forecast aggregate earnings. In another study, Call, Chen, and Tong (2008) find that analysts issuing cash flow forecasts in addition to earnings forecasts are more accurate. While both of these studies provide evidence consistent with the notion that analysts who forecast components are more accurate, they do not address whether earnings components are associated with the aggregate earnings forecasts, nor whether analysts have a more difficult time forecasting for firms whose earnings components' contain differential information than aggregate earnings about earning's persistence (issues of interest in my study).

Another stream of literature related to my study is that of pro-forma earnings. As an alternative to examining the differential persistence of earnings components, financial analysts could choose to focus only on the "relevant" portion of earnings and disregard irrelevant earnings. Perhaps unsurprisingly, studies in this stream of literature show that "pro-forma" earnings appears to be more closely associated with investors' responses to earnings announcements and with future earnings than total GAAP earnings (Bhattacharya et al. 2003; Brown and Sivakumar 2003). However, it is also clear that a simple dichotomy of earnings components into permanent "pro-forma" earnings and transitory "excluded items" is incomplete, and that there is predictive value in items excluded in pro-forma earnings calculations (Doyle et al. 2003; Landsman et al. 2007). In this study, I model earnings components along a continuum of persistence levels, and examine whether analysts' earnings prediction process is consistent with this framework, and more importantly whether or not it would be helpful for analysts to consider earnings components in this manner.

2.C. PERSISTENCE AND USEFULNESS OF EARNINGS COMPONENTS THROUGH TIME

Most academic studies examining the relation between current earnings and future earnings or the relation between current earnings and contemporaneous or future returns perform pooled cross-sectional analyses. However, there are several reasons to believe these relations may change substantially over time, especially for various components of earnings. First, investors have become more sophisticated and trading costs have declined, which could indicate a greater ability and a greater potential benefit for investors to examine and use the information provided by earnings components. Second, technology and innovation has changed the way business entities operate, causing the importance of some earnings components to differ over time. Third, and perhaps most interesting to accountants, accounting standards have changed through time, requiring different accounting treatment for the same economic transactions, which may increase or decrease the persistence of various earnings components as the transactions reflected in each component change.

Turning to the time series differences in the persistence of the aggregate earnings measure, Dichev and Tang (2008) investigate whether the persistence of earnings has decreased over the past several decades.[4] The motivation for their study is a belief that information which results from accounting standards has become less relevant because standards have resulted in a decrease in matching (of revenues and expenses contemporaneously). Dividing the sample into two subperiods (1967 to 1985 and 1986 to 2003), Dichev and Tang find evidence consistent with their claim that earnings persistence is lower in the later period. They also find that contemporaneous expenses are less correlated with revenues, the volatility of earnings has increased, and earnings changes are more negatively correlated in the later subperiod. Their results serve as a warning to both researchers and investors who may assume these statistical properties of earnings are constant through time.

According to Dichev and Tang (2008), recent accounting standards have resulted in poorer matching and contributed to reducing the persistence of earnings. At the same time, their evidence indicates that the persistence of revenue and expenses has not decreased. This raises an empirical question about whether it would be useful for investors (now more than ever) to consider future earnings a function of the persistence of revenue and expenses, rather than a function of the persistence of aggregate earnings. Dichev and Tang (2008) suggest that earnings may have become less useful over time,

[4] Interestingly, Ramakrishnan and Thomas (1998) also note—but do not analyze—a decline in the permanence (persistence) of earnings over the last 40 years.

but we have a limited understanding of whether it is now more or less important for investors, analysts, and researchers to consider the components of earnings. I contribute to the debate about the usefulness of reported accounting earnings by allowing the relations between the components and contemporaneous returns and future earnings and returns to vary through time. This analysis is timely as standard setters are considering amending the presentation and classification of earnings components in the financial statements (FASB and IASB 2008).

Chapter 3. Research questions

I conduct three sets of analyses which address different but important areas of interest in this study. First, my *preliminary analyses* confirm intuition about the associations between earnings components and both future earnings and contemporaneous returns, and also reconcile the unique methodology in this study of defining earnings components (and my more recent time period) with extant literature. Next, my *primary analyses* examine the extent to which analysts incorporate information from earnings components in their earnings' forecasts. Finally, my *supplementary analyses* provide evidence about the change in the information content and analysts' consideration of earnings components through time.

3.A. PRELIMINARY ANALYSES: INFORMATION CONTENT OF EARNINGS COMPONENTS

In preliminary analyses, I test whether earnings components better predict future earnings and whether contemporaneous returns are better associated with earnings components than aggregate earnings, which would be consistent with prior literature (i.e., Lipe 1986; Fairfield et al. 1996). However, I include a more comprehensive set of earnings components than examined in previous literature for two reasons. First, integrating an earnings decomposition based on income statement classifications with an accruals-based decomposition may result in more useful estimates of future earnings than the separate analyses based on either of the decompositions in isolation. Each framework (individually comparable to the income statement components of operating earnings in Fairfield et al. (1996) and the accrual components in Richardson et al. (2005)) may provide information that is incremental to the other. Further, the relative advantage of each framework may have changed through time, making it more defensible to include all items throughout the time series covered in my study.

Second, separately evaluating the persistence of revenues and cost of goods sold (rather than considering the summary measure, gross margin) may be particularly informative about future earnings, in part because recent research has suggested that it is useful to consider the variability and stickiness of costs following sales changes (Banker and Chen 2006). Besides revenue's usefulness for predicting future earnings, revenue has been attributed with substantial value-relevance based on its association with returns following earnings announcements (Ertimur et al. 2003; Jegadeesh and Livnat 2006; Chandra and Ro 2008). Further, Ghosh et al. (2005) report that revenue-supported earnings increases are more persistent. Finally, because this study primarily examines and discusses *analysts'* consideration of earnings components, I deem it particularly important to include revenue among the included earnings components since sales forecasts are the most prevalent disaggregated earnings item reported by analysts to I/B/E/S (Ertimur et al. 2008).

3.B. PRIMARY ANALYSES: ANALYST INCORPORATION OF INFORMATION FROM EARNINGS COMPONENTS

My primary analyses begin by examining whether analysts' forecasts and revisions are associated with the information provided by disaggregating earnings components. Previous research has linked the persistence of earnings components to analysts' forecasts using indirect proxies and has reported that the components explicitly ignored by analysts have lower persistence (Ali et al. 1992; Gu and Chen 2004). More fundamentally, analysts are widely regarded to review, interpret, and assimilate the relevant aspects of financial statements and communicate the results to investors in large part through earnings forecasts. Thus, analysts' earnings forecasts should be differentially related to the prominence of firms' various earnings components, as earnings components have predictably differential implications for future earnings. Further, analysts' forecast revisions should vary depending on whether earnings components indicate that earnings will be more or less persistent (than as indicated by aggregate earnings).

Significant results for tests of these conjectures would provide evidence that analysts incorporate information about the differential persistence of earnings components in their earnings forecasts. Alternatively, even experts such as analysts may fail to incorporate information if it is complex (Plumlee 2003). If this is the case for the persistence information in earnings components, analysts' earnings prediction process may not be well-described by the framework outlined in this study. Instead, due to their limited attention, analysts may ignore the differential persistence of earnings components and focus on other summary measures such as pro-forma earnings (Hirshleifer and Teoh 2003), earnings multiples, industry-specific growth rates, order backlogs, management forecasts, or other information.

As additional tension for this conjecture, extant research finds only very limited evidence that analysts' incentives are heavily tied to accuracy. Although a well-known study finds that the probability of turnover is positively associated with *lower* accuracy, the authors report no association between the probability turnover and absolute accuracy

(Mikhail et al. 1999).[5] Further, recent research finds no evidence that forecast accuracy is related to analysts' compensation (Groysberg et al. 2008). Thus, even if information from earnings components is obviously and abundantly useful, analyst may have limited incentives to utilize it to improve their forecasts.

I next test whether information about the differential persistence of earnings components is fully incorporated by analysts or whether analyst forecast errors are associated with the differential information from the components. Information about the persistence of these components is readily available to analysts based on financial statements reported to the public. If analysts fail to adequately and fully incorporate this relevant earnings information, forecast errors will be increasing in the extent to which the specific mix of earnings components differs from aggregate earnings (in its implication for future earnings).

Alternatively, however, forecast errors may be unrelated to differential persistence. After all, analysts *should* incorporate value-relevant information into their forecasts. To the extent this information is provided by an adequate analysis of the time-series properties of the components, analysts' earnings forecasts may reflect the information. If this is the case, any observed market mispricing of the information may result from post-revision drift (e.g., Stickel 1991) rather than the failure of sophisticated market participants such as analysts to consider and utilize the information.

[5] Absolute forecast accuracy is the focus of my study because failure to consider the persistence of components could lead analysts to make both positive and negative forecast errors.

3.C. Supplemental analyses: Earnings components through time

As discussed in the previous chapter, Dichev and Tang (2008) find that earnings have become less persistent in recent decades. Their evidence indicates that the persistence of revenue and expenses has not decreased, so they attribute the reduced usefulness of earnings to accounting standards causing poorer matching. This raises an empirical question about whether investors, analysts, and researchers (now more than ever) would benefit from considering future earnings as a function of the persistence of components.

Accordingly, I investigate the change in the usefulness of the information that can be gained from earnings components through time by examining the association between components and future earnings. Given the decrease in the persistence of aggregate earnings, earnings components' predictability of future earnings may have *relatively* increased through time.

On the other hand, earnings components may not provide more information content through time. The lower earnings persistence documented by Dichev and Tang (2008) may arise from other factors such as differences in the sample through time. Further, lower persistence of GAAP earnings does not necessarily imply that components have become more informative. Through time future earnings may have simply become more difficult to predict, even when considering the differential persistence of components.

Finally, I investigate whether analysts' use of information from earnings components has changed through time. If the predictability of earnings components has improved and analysts do not recognize this, the relation between analyst forecast errors and the information from components may increase. On the other hand, analysts may recognize the increasing importance of earnings components and place more emphasis on this information, which would decrease the relation between forecast errors and the information from earnings components. This is especially true in recent years, as Regulation FD has restricted analysts' access to direct, unfiltered information from management (which may be firm-specific and unrelated to the average persistence of components). Thus, I test whether the relation between analysts' forecast errors and the information from components has changed through time.

Chapter 4. Research design, key variables, and descriptive statistics

4.A. RESEARCH DESIGN

I begin by defining "earnings components" and describing how such components may be incrementally informative about future earnings relative to aggregate earnings. Early studies examining associations between "earnings components" and returns and future earnings defined earnings components as income statement line items (Lipe 1986; Fairfield et al. 1996). However, earnings components can also be thought of as earnings provided by cash or accruals (Sloan 1996) or those that are transitory, permanent, or price-irrelevant (Ramakrishnan and Thomas 1998), discretionary or non-discretionary (Subramanyam 1996), expected and unexpected, recurring and non-recurring, normal and abnormal, etc.

This study includes a broad set of components based on an integration of two frameworks from prior literature—1) income statement line items and 2) balance sheet "accruals." Income statement line items are used in the traditional framework for examining earnings components with differential levels of persistence that can be used to predict future earnings (Fairfield et al. 1996). In addition to income statement line items, the persistence of balance sheet accruals may have an additional limited association with future earnings. This suggests that the accrual and cash flow components of traditional income statement line items may have differential persistence. Researchers have begun to examine whether disaggregation among accrual components is helpful for predicting future earnings and cash flows (Barth et al. 2001; Richardson et al. 2005). Standard setters have even considered requiring a reconciliation schedule in the financial statements that specifically disaggregates income statement line items into the portion received by cash or accrued (FASB 2008).

Further, it seems quite appropriate to consider both income statement and balance sheet "accrual" frameworks as, over time, the value relevance from one may be improved relative to the other due to economic conditions, business practices, or accounting innovations. As an example of how business practices could influence this relation, consider how *Just-in-Time* inventory reduced inventory levels of some firms, which could have changed the signaling effect of various accounting metrics in different ways (Boyd et al. 2002) . As an example of an accounting innovation, consider that *LIFO* inventory valuation results in a cost of goods sold earnings component that more fully explains equity values than the comparable component that was the result of *non-LIFO* inventory accounting (Jennings et al. 1996). Thus, allowing the persistence estimates of both income statement and accrual components to vary across time may be important for forecasting future earnings or explaining returns.

For the income statement components, I select items with substantial data availability that aggregate to earnings before extraordinary items (COMPUSTAT Annual Item "IB"). When possible, I decompose these components into the portion received as or paid in cash and the (non-overlapping) portion accrued. I utilize all selected components for my empirical tests.[6] A complete list of these components and the data restrictions imposed upon construction is discussed below. Dividing each income statement component (revenue, cost of goods sold, etc.) is admittedly imperfect as the

---

[6] An alternative design choice would be to retain only components with predictive ability for future earnings, but many components are correlated making this methodology difficult.

cash and accrued portions as they are not explicitly reported and can only be estimated. However, this methodology is easier to interpret than an alternative, such as including all income statement components (which sum to net earnings) and all accruals (which sum to change in cash).

By including the level of each earnings component as an independent variable, the persistence of the magnitude of each component is retained, which I anticipate will be most directly relevant for forecasting future earnings. However, I also include the change in each component (averaged over the prior two years) in the event a significant trend is persistent and would thus be useful to forecast future earnings. As an example of how this may influence earnings persistence, consider two firms which the same level of one earnings component, but where the second firm had a large change in the component. While the level of the earnings component suggests the same level of persistence, a positive (negative) coefficient on the change in the components will indicate higher (lower) earnings persistence for the second firm.

Results in prior research are consistent with the usefulness of changes in earnings and the changes in components. As shown by Easton and Harris (1991), earnings changes are partially explained by prior earnings changes, even controlling for earnings levels. Suggesting the usefulness of at least one earnings component, Schmidt (2006) finds that the tax change component of earnings (defined in his study as the change in effective tax rate) is positively associated with future earnings. Thus, changes in earnings' components could also explain future earnings. [7]

The trend variables are included despite the fact that many may not be statistically different from zero or economically important after controlling for the average level. Because of the nature of some earnings components, some may even be near multi-collinear. That is, there may be a high correlation between certain predictors (earnings components) because such predictors capture a similar construct. If so, this could lead to improper conclusions that certain variables are insignificant. As a result, I do not place reliance on the tests of the significance of the coefficients from the related regressions, and as previously discussed, I do not remove any components for which coefficients are "insignificant." Instead, I retain all variables as this concern should not degrade the ability of the components to forecast (Belsley 1984; Ramanathan 2002).

To summarize, I estimate the following regression (variables are all scaled by prior-year total assets, and are defined below the equation):

$$EARNINGS_{i,t} = \alpha_1 + \sum_{j=2}^{n+1} \alpha_j CC_{i,j,t-1} + \sum_{k=n+2}^{n+p+1} \alpha_k ACC_{i,k,t-1} + \sum_{l=n+p+2}^{2n+p+1} \alpha_l AVG\Delta ISC_{i,l,t-1} + \varepsilon_{i,t} \qquad (1)$$

> $EARNINGS_{i,t,}$ is earnings before extraordinary items for firm i for fiscal year t.[8]

[7] In untabulated analysis, I confirm that although the change in components are useful, the main inferences in this study are not driven by the change in components. That is, the results presented are robust to using only the levels coefficients in equation (1).

[8] For robustness, I also define *EARNINGS* as net income, adding extraordinary items and discontinued operations as components in the disaggregation. Results are qualitatively similar.

$CC_{i,j,t-1}$ is the j^{th} cash portion of firm *i's* income statement components for the year ending *t-1*. The income statement components [$j \in (2, n+1)$] are listed below. For the primary estimation, n=7 as I utilize eight income statement components, but classify *Special Items* as an accrual component only.

$ACC_{i,k,t-1}$ is the k^{th} accrual portion of firm *i's* income statement components for the year ending year *t-1*. The components are listed below. For the primary estimation, p=8 as I utilize eight income statement components.

$AVG\Delta ISC_{i,l,t-1}$ is the average two-year annual change in firm *i's* income statement components, where the average is taken for the two fiscal years ending in year *t-1*.

Specifically, the earnings components used for this study are disaggregated from income statement components and categorized and discussed in terms of their cash and accrued portions. The three columns below indicate the details of the classifications, where the source data is from COMPUSTAT Xpressfeed and COMPUSTAT mnemonics are in non-italicized capital letters:

Income Statement component	Cash Portion	Accrual Portion
Sales (SALE)	SALE-ΔRECT	ΔRECT
Cost of Goods Sold (COGS)	COGS-ΔINVT	ΔINVT
SG&A (XSGA)	XSGA-ΔAP	ΔAP
Depreciation (DP)	DP+ΔPPENT	DP
Interest (XINT)	XINT	ΔDLTT+ΔDLC
Non-operating (NOPI)	NOPI-ΔVarious	ΔVarious
Income tax (TXT)	TXT-ΔTXDB	ΔTXDB
Minority Interest (MII)	MII-ΔMIB	ΔMIB
Special Items (SPI)	n/a	SPI

ΔVarious is defined as -ΔACO+ΔLCO-ΔIVAEQ-ΔAO+ΔLO-ΔIVAO, where ACO=other current assets, LCO=other current liabilities, IVAEQ=equity method investments, AO=other assets, LO=other liabilities, and IVAO=other investments. As illustrated above, Special Items is retained in aggregate as further disaggregation is not practical.

In addition, I make several assumptions and constraints when categorizing these variables. First, the cash and accrual portions do not sum to the income statement component for depreciation or interest. A simplifying assumption is made that the income statement portion is all cash (in the case of interest) or all non-cash (in the case of depreciation). However, the information for the "non-cash portion" of interest and the "cash" portion of depreciation (which are actually changes in balance sheet items that are expected to directly affect future income through these income statement items). Second, I require that earnings before extraordinary items (IB) and Sales (SALE) be non-missing. Other missing components are set to zero, but to ensure this assumption is reasonable I drop any observation for which the aggregation of income statement components is unequal to earnings before extraordinary items.[9] Finally, current and prior-year total assets (AT) must not be less than $10 million.

To accommodate the possibility that the predictability of these components changes over time, I estimate equation (1) annually using five-year rolling windows.[10] To reduce the influence of outliers on the coefficient estimates from equation (1), I do not utilize observations with an absolute value of an earnings component greater than two times the firm's assets, observations for which earnings or a change in any component has an absolute value greater than the firm's total level of assets, and observations for

[9] I allow the aggregation to vary by up to $10,000 to allow for differential extents of rounding by COMPUSTAT.

[10] For example, for the five-year rolling window ending in 1995, the coefficients are estimated using values for the dependent (independent) variables from years t=1991 to 1995 ($t-1$=1990 to 1994). See Figure 1.

which the studentized residuals when estimating this regression has an absolute value greater than two.[11] I do not fully discard these observations but retain them for all out-of-sample and subsequent tests.

I require eight years of data to obtain any out-of-sample estimates, and estimate regressions using equation (1) for firms with COMPUSTAT fiscal years ending in 1969 through 2006. Therefore, I have out-of-sample earnings predictions for fiscal years ending between 1970 and 2007. I also utilize a second window of earnings predictions for fiscal years ending between 1994 and 2007. This second window is chosen to correspond with my sample of analyst forecasts, which is discussed in chapter 6. COMPUSTAT defines firms with a fiscal year-end month during January through May of the subsequent year as having a fiscal year equal to the previous calendar year. Also note that although I use eight years of COMPUSTAT data to estimate rolling regressions, for a given firm-year observation, I use a minimum of four and a maximum of five years of data (*t-2* through *t-1* for the independent variables scaled by prior year assets—*t-2* is required so that at least one "change" can be calculated—though I also use *t-3* components if available to calculate the average change, scaling in that case by *t-4*

[11] In a further attempt to stabilize the coefficients, I estimated equation (1) separately for each Fama and French (1997) industry. However, this did not improve the stability of the coefficients but instead resulted in a higher coefficient of variation in the in-sample forecast error. Based on this and recent research reporting that incorporating industry information does not improve forecasting of future profitability (Fairfield et al. 2009), I perform this estimation at the economy-wide level.

assets—and t for the dependent variable). I provide an illustration to clarify this in Figure 1.[12]

As a benchmark, I estimate an alternative prediction model lacking information from earnings components across the same time window (five-year rolling regressions) and using the same influential-outlier correction as used in the estimation of equation (1):

$$\begin{aligned}EARNINGS_{i,t} &= \alpha_1 + \alpha_2 PROFIT_{i,t-1} + \alpha_3 EARNINGS_{i,t-1} + \\ &\alpha_4 PROFIT_{i,t-1} * EARNINGS_{i,t-1} + \alpha_5 AVG\Delta EARNINGS_{i,t-1} + \varepsilon_{i,t}\end{aligned} \quad (2)$$

PROFIT is an indicator variable indicating whether $EARNINGS_{i,t-1}$ is positive and $AVG\Delta EARNINGS_{i,t-1}$ is the average annual change in $EARNINGS_i$ over the two years ending $t-1$. I include *PROFIT* and its interaction with $EARNINGS_{i,t-1}$ because loss firms are known to have different aggregate earnings persistence than profit firms (Hayn 1995). As I discuss below, including the *PROFIT* indicator and its interaction when estimating equation (2) but not when estimating equation (1) is intended to be a conservative design choice that may bias against finding that earnings components are more informative than aggregate earnings.

4.B. KEY VARIABLES

I construct a summary measure to capture the extent to which the earnings component model generates a prediction of future earnings that varies from a prediction

[12] While including five years of data and lagged earnings components for each firm in the earnings components and aggregate earnings specifications helps to stabilize the coefficients, it potentially results in correlated error terms due to a lack of independence between the observations. Accordingly, as a robustness test, I re-estimate equations (1) and (2) using a generalized linear model with an AR(1) structure and firm fixed effects. Using these re-estimated coefficients on earnings components and changes (for equation (1)) and aggregate earnings and changes (for equation (2)), I confirm that the main inferences discussed in later chapters are not affected.

based on the aggregate earnings model. This measure is referred to as differential component information (*DCI*):

$$DCI = \left| \frac{\widehat{EARNINGS}_{i,T+1\,COMP} - \widehat{EARNINGS}_{i,T+1\,INC}}{\widehat{EARNINGS}_{i,T+1\,INC}} \right| \tag{3}$$

$\widehat{EARNINGS}_{i,T+1\,COMP}$ is the predicted value of earnings based on a fitted value using coefficient estimates from equation (1) and the values of the firm's earnings components (and changes) for time *T* (*T* is the final year in the rolling-window estimation). For $\widehat{EARNINGS}_{i,T+1\,INC}$, I use coefficient estimates from equation (2) to compute the predicted value. Because I allow profit and loss firms differing persistence levels when estimating equation (2) but not when estimating equation (1), this measure does not fully capture the extent to which the components may be differentially persistent for loss firms compared to profit firms, biasing against finding that the components are informative relative to aggregate earnings. Because a given value of $\widehat{EARNINGS}_{i,T+1\,INC}$ that is extremely close to zero may cause an inappropriately large value for *DCI*, I delete any observation for which the calculated value of *DCI* is greater than the 99th percentile. I also delete firm-year observations for which the two predictions have opposite signs (11,004, approximately 6% of firm-years).

The reference point for *DCI* is the average decomposition of the components for the sample at each estimation window. By construction, a high value indicates that the weighted average of the firm's earnings components and the components' implied persistence is different than the implied persistence of aggregate earnings. If a firm has the same relative proportion of all earnings components as the average firm, its earnings components and aggregate earnings will predict the same level of future earnings, and *DCI* will equal zero. *DCI* will be greater than zero when the relative proportion of the firm's earnings components differs from the average firm.[13]

I use the measure *DCI* to quantify the degree of differential information about the persistence of a firm's earnings components relative to the persistence indicated for a firm's aggregate earnings. In the example that follows, I illustrate what is intended to be captured by this measure. This example is highly simplistic, as I utilize many more than two earnings components in my actual analyses.

Consider a firm with two components, one "transitory" and one "permanent." Year A coefficients on these components are 0 and 1.2, respectively. Average earnings persistence is 1.05. In year A, the firm has \$100 in transitory earnings and \$300 in permanent earnings. Predicted values of earnings in Year B, then, are \$360 using information from the components and \$420 using only aggregate earnings.

$$DCI = |(360\text{-}420)/420| = 0.14.$$

Consider another firm with the same two components, one "transitory" and one "permanent." Year A coefficients on these components are 0 and 1.2, respectively. Average earnings persistence is 1.05. In year A, the firm has \$50 in transitory earnings and \$550 in permanent earnings. Predicted values of earnings in Year B, then, are \$660 using information from the components and \$630 using only aggregate earnings.

[13] Because equation (2) assigns different coefficient values for profit and loss firms, the benchmark differs depending on whether the firm is a profit or loss firm.

> *DCI* = |(660-630)/630| = 0.05, indicating substantially less (relative to the first firm) differential information of the firm's earnings based on a weighted-average of the persistence of each of its components.

Some of my analyses require an estimation of whether earnings components would indicate **more** or **less** persistence than aggregate earnings. For these, I use the following measure of signed differential component information (*SDCI*), where a high value indicates that an analysis of the components reveals that earnings is more persistent than an analysis of aggregate earnings reveals:

$$SDCI = \frac{\widehat{EARNINGS}_{i,T+1\,COMP} - \widehat{EARNINGS}_{i,T+1\,INC}}{\widehat{EARNINGS}_{i,T+1\,INC}} \tag{4}$$

The sign of *SDCI* reveals whether the earnings components model suggests earnings is "more persistent" or "less persistent" rather than "higher" or "lower" because the prediction represents a weighted-average of the persistence (and actual values) of the components. Similarly to my unsigned measure, I delete observations for which the calculated values may result from inappropriate scaling—in this case the 1st and 99th percentile.

The computation of *SDCI* is illustrated with a continuation of the numerical example above. Similarly to *DCI*, *SDCI* captures the variability of the persistence. However, it is signed so as to capture directional information (i.e., the components reveal that earnings is *more or less* persistent than aggregate earnings reveals).

For the first firm:

> SDCI = (360-420)/420 = -0.14, revealing that an analysis of the components indicates lower estimated persistence of earnings than an analysis of aggregate earnings alone.

And the second:

> *SDCI* = (660-630)/630 = +0.05, revealing that an analysis of the components indicates higher estimated persistence of earnings than an analysis of aggregate earnings alone.

Considering the implications of this example for both *DCI* and *SDCI*, an "average" firm would have 87.5% (1.05/1.20) permanent earnings and 12.5% transitory earnings. A firm with an "average" mix of components will have values of *DCI* and *SDCI* equal to zero. Because the first firm in the example above has more income concentrated in transitory (low-persistence) components, *DCI* is greater than zero and *SDCI* is less than zero. Conversely, because the second firm has relatively more income concentrated in permanent (high-persistence) components, both *DCI* and *SDCI* are greater than zero.

When constructing this measure, two research design decisions are made with regard to scaling. First, as previously discussed, the earnings measure is scaled by assets when estimating equations (1) and (2), as are all the components of earnings. This research design choice (using assets as a deflator) follows recent forecasting and earnings persistence research (e.g., Richardson et al. 2005; Soliman 2008; Dichev and Tang 2009).[14] As with other research design choices related to equation (1), the intent is to allow earnings components to be useful for forecasting and utilizing them in such a way as to reduce noise. Besides assets, I also consider using equity or shares outstanding as deflators. In untabulated analysis, I find that the absolute in-sample forecast error (the

[14]Soliman (2008) uses *net operating assets* as the deflator and forecasts return on net operating assets (RNOA). However this metric does not include several of the income components which are potentially important in this study (interest, special items, etc.), so I use total assets.

absolute value of the residual) is both statistically and economically greater for these alternative deflators. Assets appears to be the most reasonable deflator among the alternatives considered.

Second, *DCI* (*SDCI*) is a ratio in which the numerator is the absolute (signed) difference between the predictions of the earnings components model and aggregate earnings model. The denominator of this ratio is the earnings prediction using the aggregate earnings model. As constructed, the measure is equivalent to one minus a ratio of the earnings components model's prediction to the aggregate earnings model's prediction. By subtracting the ratio from one and taking the absolute value, *DCI* and *SDCI* are constructed so that values close to zero indicates the two predictions are similar, or in other words that there is no differential information when considering the components. The scaling is convenient as it allows for an interpretation of the value as a percentage difference from the benchmark aggregate earnings model.[15] However, this measure could have been scaled alternatively, such as by realized earnings, inversely (that is, as the difference divided by $\widehat{EARNINGS}_{i,T+1\,INC}$), or not at all. I am aware of no bias that this design choice makes on my results, but I utilize annual decile ranks when making inferences.

4.C. DESCRIPTIVE STATISTICS

Table 1 reports descriptive statistics for the forecasting sample, *T*=1969 to 2006. Panel A provides the distribution of the income statement line items from COMPUSTAT

[15] For example, if $\widehat{EARNINGS}_{T+1\,INC}$ = 0.25 and $\widehat{EARNINGS}_{T+1\,COMP}$ = 0.30, then *SDCI* = 0.20 as the prediction from earnings components model is 20% higher than the prediction from the aggregate earnings model.

(scaled by prior-year assets) for the sample. As expected, sales and cost of goods sold represent the largest and second largest income statement items—with mean (median) values of 121% (102%) and 86% (64%) of assets, respectively. Selling, general, and administrative expenses represents the only other over five percent of assets—with a mean (median) value of 22% (14%) of assets. Further, the 25th to 75th percentiles of special items and minority interest are zero, indicating that these two items they are non-zero less than 50 percent of the time.

Panels B and C of table 1 report descriptive statistics for the "cash" and "accrued" portions of these income statement components, respectively. Across the cash and accrued portions, as expected, the cash portion is dominant in most cases. No mean or median accrued portion of any income statement components is more than five percent of assets.

Finally, panel D reports the average two-year change in each of the income statement line items (scaled by lagged assets). The absolute value of the median average change in each of the components is less than 0.001% of assets. However, the average change in sales (cost of goods sold) are -2.8% (-1.7%), which may indicate that growth in the dollar amount of these earnings components are slightly outpaced by growth in total assets, on average.

In table 2, I report the average coefficients for each component from the rolling regressions for the components model (equation (1)) and the aggregate earnings model (equation (2)). The reported coefficients are averages from 38 annual regressions, which each span a five-year window (see figure 1).

Panel A of table 2 reports the average magnitudes of the earnings component "levels," as disaggregated into their cash and accrual portions. The sign of the coefficients can be ignored when interpreting the coefficients, but some are positive while others are negative because COMPUSTAT codes sales, special items, and non-operating income as positive when income-increasing, while all other components are coded positive when income-decreasing. Also recall that I have made a simplifying assumption that special items and depreciation are all accrued and interest is all cash, but have introduced an "accrued" portion of interest which represents the effect of increasing debt, and a "cash" portion of deprecation which represents the effect of making additional capital expenditures. The "accrued" portion of interest represents the future income reduction (only 0.0179) that can be attributed to by an increase in debt. Capital expenditures also results in a decrease in future earnings (0.0260), presumably by means of future depreciation.

In general, variation is present in the magnitudes of the coefficients for the levels variables, with average coefficients on operating components higher than coefficients on non-operating components, which are higher than coefficients on special items. The cash and accrual portions of sales, cost of goods sold, SG&A, and minority interest, as well as interest expense (all cash) are between 0.7128 and 0.7826, so these are the most persistent components of earnings. Depreciation (all accrued) translates into a future earnings-decrease of 0.6592. This may be lower than the other operating components due to the existence of accelerated depreciation methods (which may cause a lower recurrence of depreciation or provide a positive future income benefit which would offset the future depreciation recurrence).

Most interestingly, the cash vs. accrual portions of many of the income statement items are remarkably similar. This result is noteworthy given the popular perception that accruals are "less persistent" than cash flows.[16] Among the operating variables excluding depreciation as discussed above, the "accrual" portion of sales has the lowest average coefficient (0.7128). However, the accrual portion of cost of goods sold has the highest coefficient (0.7826), and this portion is greater than the cash portion of this income statement item (0.7267). Statistically, the average differences between the cash and accrual portions (reported in the last column of panel A) are significantly different with the exception of SG&A.

In panel B of table 2, the average coefficients on the "change" components have the opposite sign as the levels from panel A with markedly lower magnitudes, indicating the tendency for earnings components to revert after large increases or decreases. Also, the changes in income taxes and non-operating income except the most substantial reversion (with coefficients of 0.1512 and 0.1370, respectively). This indicates that in addition to being less persistent than many of the other components (based on the results in panel A), innovations in these two components have the greatest tendency to revert to prior levels. This can be easily understood for non-operating items, as a one-time gain or loss would not recur. It is less clear why a large change in income taxes would be followed by substantial reversion in the subsequent period. Although this may reflect the

[16]Another paper which provides alternative evidence on this perception is Francis and Smith (2005).

effect of one-time tax items, another potential explanation is that when firms achieve greater general profitability and also pay more in taxes, they subsequently have higher levels total net earnings (relative to firms that do not experience an increase in their tax component).

In panel C of table 2, I report the average coefficients on the terms from equation (2). Profit is a differential intercept term for the earnings of firms whose previous earnings is positive (the intercept term for loss firms is untabulated and insignificant). The average coefficient is 0.0081, or 81 basis points of one percent of assets. Earnings for loss firms have persistence of 0.4396, while earnings of profit firms have persistence of 0.7813 (0.4396+0.3417). Unsurprisingly, like changes in earnings components (panel B), changes in total earnings is associated with some reversion, as the coefficient on the average change in prior earnings is -0.0811.

Panel D of table 2 reports descriptive highlights for fit statistics from the estimation of rolling regressions for the earnings components model (equation (1)) and the aggregate earnings model (equation (2)). The average R-squares are 0.7134 and 0.6630, respectively. The R-square of the aggregate earnings model is largely attributable to the differential slope coefficients for profit vs. loss firms, a feature absent from my components model but apparently more than overcome by information about the persistence of each component.

As presented in Panel E, the interquartile range of my two summary measures of interest, *DCI* and *SDCI*, are 0.0690—0.3500 and -0.1338—0.1797, respectively, exhibiting enough variation in the data to observe an effect, if present. Medians are

0.1598 (*DCI*) and 0.0336 (*SDCI*). *SDCI* is greater than zero because I exclude any observations in which the numerator and denominator are of different signs, all of which would have been negative for *SDCI*.

Chapter 5. Preliminary analyses: The usefulness and information content of earnings components

5.A. Information content of earnings components as indicated by out-of-sample forecast errors

To examine whether future earnings are better predicted when considering the differential persistence of various earnings components than when considering only aggregate earnings, I obtain coefficient estimates from equation (1) in each year *T* using data from years *T-4* to *T* and calculate the expectation for year *T+1* earnings by multiplying these coefficient estimates by the year *T* earnings component values. Component model forecast errors are then defined as the predicted value from this procedure minus the actual future earnings (before extraordinary items, scaled by prior year total assets). I compare these model forecast errors to errors from predictions based on my main benchmark, rolling regression estimation of equation (2).

In addition to my main benchmark (the aggregate earnings specification), I compute predictions and errors from three additional benchmark forecasting models and similarly examine their ability to predict future earnings—1) a model in which *Earnings/Assets* follows a random walk, 2) a model based on decomposing earnings into operating and non-operating components (Fairfield et al. 1996), and 3) a model based on decomposing earnings into its cash and accrual subcomponents (Sloan 1996; Collins and Hribar 2000).

The Fairfield et al. (1996) benchmark is based on the model in their study with the best out-of-sample predictive ability (described as the "OPINC" model in their figure 1 and their tables 2, 3, and 4). Its components include operating income, non-operating income and taxes, special items, and non-recurring items. I utilize only the first three components in my replication of this benchmark as non-recurring items is not a part of my dependent variable, and I scale by prior assets rather than equity for reasons discussed in chapter 4. To define accruals vs. cash flows, I follow Collins and Hribar (2000) when cash flows from operations is available and Sloan (1996) otherwise. For each of these benchmarks (except random walk), I use the same methodology discussed in chapter 4 to control for the influence of outliers when estimating the predictive coefficients from rolling regressions.

I report the average raw and absolute out-of-sample forecast error for each of my predictive models in table 3. Among the raw forecast errors of the models, the random walk of *Earnings/Assets* is the closest to zero (-0.0027), but has the highest standard deviation (0.2335). For my inferences, however, I focus on the average absolute forecast errors. Relative to the random walk model, the average absolute error is lower using the aggregate earnings model and even lower using the components model (0.0564, 0.0522 and 0.0497, respectively). The average improvement from the aggregate earnings to the earnings components model is 0.0025, which is significant at the one percent level (t=17.43). The Fairfield et al. (1996) disaggregated earnings model performs better than the aggregate earnings model (t=13.22, untabulated) but not as well as the earnings components model (t=12.82), contrasting with the result from Fairfield et al. (1996) that "further disaggregation" (from their best-performing model) worsens out-of-sample predictability. The accruals model slightly underperforms the aggregate earnings model (t=1.97, untabulated).

At the median, no model besides the aggregate earnings model performs better than the random walk model; however, this appears to be a full-sample phenomenon driven by firm-year observations which have substantially close predictions between the models. Using the 80% of observations for which the difference between the predication based on a random walk and $\widehat{EARNINGS}_{COMP}$ differ by at least 0.002, median analysis indicates an improvement for all predictive models above the random walk model, in a pattern similar to the reported full-sample results for the means, which are all significant at the one percent level.

Economically, an improvement of 0.0025 from the aggregate earnings to the earnings components model equates to \$0.6 million for the median firm (0.0025 times \$241 million, the assets for the median firm in my sample). This is approximately 8.5% of median earnings (\$7 million in my sample). Thus, the earnings components model used in this study appears to be helpful at predicting future earnings by using the historical persistence of the various earnings components.

Finally, in an alternative specification to test the usefulness of the earnings components model relative to the aggregate earnings model for forecasting future earnings, I regress the signed error from the aggregate earnings model (i.e., $EARNINGS - \widehat{EARNINGS}_{INC}$) on the signed difference between the predictions of the two models (i.e., $\widehat{EARNINGS}_{COMP} - \widehat{EARNINGS}_{INC}$). I find that the coefficient on the difference is positive and highly significant (untabulated).

5.B. INFORMATION CONTENT OF EARNINGS COMPONENTS AS INDICATED BY STOCK RETURNS

Next I examine the relation between contemporaneous returns and earnings. This is done to establish whether investors' reactions are more consistent with an expectation that earnings are a function of the persistence of its components or a function of the persistence of aggregate earnings. I obtain earnings announcement dates from the COMPUSTAT quarterly events file and retain the earnings announcement date for the fourth fiscal quarter for each firm-year.

Returns contemporaneous with earnings ($EARNRET_T$) are measured using the CRSP monthly file, and defined as the twelve month buy-and-hold returns ending at the end of the month of the earnings announcement dates, where the buy-and-hold return is calculated as the product of one plus the monthly returns on CRSP for each month in the estimation window, the quantity minus one.[17] Market and size-adjusted returns are calculated by subtracting the CRSP value-weighted or decile average return from each of the firms' monthly returns. Return data is available for firms with fiscal years ending between June 1968 and July 2007.

I estimate a cross-sectional regression of contemporaneous returns on the earnings news, where the news is defined as actual GAAP earnings minus a prediction of current earnings based on the out-of sample future earnings prediction from equation (1). However, I first decompose this news into two pieces—1) the surprise based on actual GAAP earnings minus an earnings prediction based on Equation (2), and 2) the

[17] When the earnings announcement date for the fourth quarter is not available from the COMPUSTAT quarterly events file, the window for the contemporaneous return is set equal to the twelve months ending at the end of the third month following the fiscal year end.

incremental surprise to an investor who used the components model rather than the aggregate earnings model. The regression of contemporaneous returns on the two pieces of earnings news follows:[18]

$$\begin{aligned}
&EARNRET_{T+1} = \beta_1 + \beta_2(EARNINGS_{T+1} - \widehat{EARNINGS}_{T+1\,INC}) + \\
&\beta_3(\widehat{EARNINGS}_{T+1\,INC} - \widehat{EARNINGS}_{T+1\,COMP}) + \beta_4 LARGESURPRISE + \\
&\beta_5 LARGESURPRISE * (EARNINGS_{T+1} - \widehat{EARNINGS}_{T+1\,INC}) + \\
&\beta_6 LARGESURPRISE * (\widehat{EARNINGS}_{T+1\,INC} - \widehat{EARNINGS}_{T+1\,COMP}) + \varepsilon
\end{aligned} \tag{5}$$

The variable *LARGESURPISE* is an indicator variable set to one when the total news ($EARNINGS_{T+1} - \widehat{EARNINGS}_{T+1\,COMP}$) is in the top or bottom decile. I include this in an attempt to control for the non-linearity of earnings response coefficients (Freeman and Tse 1992). As reported in table 4, I find that the cross section of contemporaneous returns is explained by both the surprise from the aggregate earnings model *and* the additional surprise had investors used the components to develop their expectations. For non-extreme earnings surprises, the size-adjusted return on an earnings surprise based on the aggregate earnings model is 4.3503, or approximately 4.35% based on an additional one percent surprise (recall that *EARNINGS* is scaled by assets), controlling for the incremental surprise. However, the incremental news based on the earnings components is also significant, 3.6085, or approximately 3.61% based on additional one percent incremental surprise. Thus, I report evidence that the market response to earnings

[18] Unlike the preliminary analysis examining predictability of future earnings, I do not test the contemporaneous return associations with surprises from earnings predictions using alternative models. The only study I am aware of that examines the association between contemporaneous returns and earnings components is Lipe (1986); however, the model in that study is a firm-specific time-series and is not reasonably comparable to the predictive models in this study.

surprises is consistent with at least some investors' using earnings components to form expectations for future earnings.[19]

I conclude my preliminary analyses by providing some additional descriptive statistics about the forecasting sample. Specifically, I investigate some cases in which the earnings components model in this study may be particularly helpful relative to the aggregate earnings model. These results may be of interest to analysts, other financial statement users, or researchers. In panel A of table 5, I report average levels of commonly-reported firm characteristics for the entire sample, and then partition the sample based on the level of improvement provided by the earnings components model relative to the aggregate earnings model. When reporting these statistics, all continuous variables have been winsorized at the first and 99th percentile. Definitions of the firm characteristics follow (COMPUSTAT mnemonics in quotations and non-italicized capital letters, all at time *T*):

> *Total Assets* is as defined by COMPUSTAT (Annual item "AT").
>
> *Book/market* is book equity ("CEQ") divided by market capitalization ("PRCC_F"*"CSHO").
>
> *Return on assets* is income before discontinued operations ("IB"), scaled by total assets ("AT").
>
> *Special items indicator* is an indicator variable equal to one if special items ("SPI") is non-zero, or zero otherwise.

[19] F-tests of whether the coefficients on these surprise components are different are significant at conventional levels in each return specification. Fama-MacBeth (1973) annual regressions estimating equation (5) provide similar inferences. However, an alternative way to test this, regressing the returns on the surprise from each model individually, is inconclusive. The r-square and coefficients in these specifications are similar. This appears to result from a shift in the relative importance of each model over time, which I investigate further in chapter 7.

Growth in sales/assets is the average prior two-year change in "SALE"/"AT" (one of the earnings components used in Equation (1)).

Loss indicator is an indicator variable set equal to one if "IB" is less than zero, zero otherwise.

Accruals is defined using COMPUSTAT data follow Collins and Hribar (2000) when cash flows from operations ("OANCF") is available and Sloan (1996) otherwise, scaled by total assets "AT."

In the final column of panel A, I report the percentage difference for high-improvement firm-observations relative to low-improvement firm-observations. No differences are particularly notable except that high-improvement firms on average have a lower return on assets and a larger number of them are loss firms than low-improvement firms. An interpretation of this finding is that analysis of earnings components may be more helpful for firms that are less profitable (or not profitable). This is an interesting finding, considering that the aggregate earnings model explicitly allows for profit and loss firms to have different levels of earnings persistence, while the earnings components model does not. This limitation of the earnings components model is apparently overcome in large part by allowing earnings components to have differing levels of persistence.

In panel B of table 5, for each of 22 industry groupings (based on SIC codes), I report the mean and median observed levels of the improvement provided by the earnings components model relative to the aggregate earnings model. The most notable improvement can be observed in the manufacturing and pharmaceutical industries, as well as computers, transportation, and some others. This indicates that there may be some homogeneity among the firms in these industries with respect to the stability of the persistence of each earnings component, and could also arise due to the high number of these firms present in my sample. Not surprisingly, information about the cross-sectional persistence of earnings components appears to be less useful in financial industries and utilities, among others. This may arise if the classification and aggregation of earnings components from the financial statements by COMPUSTAT is not as informative for these firms.

Chapter 6. Primary analyses: Analysts' use of information from earnings components

After establishing the usefulness of earnings components in predicting future earnings, I evaluate how analysts use this information. In this section, I provide evidence addressing three research questions. First, I examine whether analysts' forecasts are associated with the information provided by disaggregating earnings into components. Second, I test whether the differential persistence of earnings components (relative to aggregate earnings) is associated with analyst forecast errors. Third, I analyze the association between the improvement from the earnings components model and analysts' forecast errors. Together, these tests investigate the extent to which analysts consider the variation in the persistence of earnings components.

I collect analyst forecasts for 30 days following fiscal year-end earnings announcements based on earnings announcement dates from I/B/E/S. I include one-, two-, three-, and four-quarter-ahead forecasts, retaining the first forecast revision following an earnings announcement for each analyst-firm-horizon. I restrict my sample collection to estimates made for quarters ending during fiscal 1995 to 2007 based on a substantial increase in the availability of quarterly analyst forecast data beginning in 1995. Quarterly forecasts are selected because quarterly forecasts are updated more quickly and more often than annual forecasts both in general throughout the quarter and specifically following earnings announcements (thus, they are more current and seem to have more attention paid to them), at least in recent years. However, for completeness, I also perform tests and tabulate results for my primary analyses based on analysts' one-year ahead annual forecast revisions made in the first 30 days following the fiscal year-end earnings announcement.

I also obtain each analyst's time *t* surprise (actual – most recent forecast, the quantity scaled by CRSP stock price at the end of the month preceding the estimate date), and necessary data to compute the analyst's time $t+h$ forecast error.[20] I group forecasts into the horizon, the number of quarters relative to the earnings announcement [$h \in (1, 4$ quarters)]. This controls for the time between the revised forecast and the subsequent earnings announcement. Figure 2 illustrates the timeline for the forecasts and revisions used in this study.

6.A. ARE FORECASTS RELATED TO THE PERSISTENCE OF EARNINGS COMPONENTS?

As an initial test of whether analysts' incorporate the information content of earnings components, I regress analyst forecasts of future earnings on the *most recently reported* components of earnings mirroring equation (1), as follows:

$$FORECAST_{r,i,t+h} = \alpha_1 + \sum_{j=1}^{n+1} \alpha_j CC_{i,j,t} + \sum_{k=n+2}^{n+p+1} \alpha_k ACC_{i,k,t} + \sum_{l=n+p+2}^{2n+p+1} \alpha_l AVG\Delta ISC_{i,l,t} + \varepsilon_{i,t+h} \qquad (6)$$

where the dependent variable represents the level of the *FORECAST* of analyst *r* making a revision in his or her prior estimate for the future earnings of firm *i*, *t* is the most recent fiscal year for which an earnings announcement is made by firm *i*, *h* is the number of quarters-ahead for which the revision is made, and the independent variables are the previously-defined earnings components from year *t* which may be predictably related to

[20] There is no distinction between *t* and *T* when referring to analyst forecasts and revisions, because no rolling windows are used.

future earnings.[21] I examine the R-square from this regression, and compare it to a benchmark regression mirroring equation (2). Although my main empirical specification is void of control variables, it is reasonable to predict that certain analyst characteristics or firm characteristics may lead to a greater or lesser extent of incorporation of information from the components. I do not include such interactive effects, but instead predict an "on average" relation between the various components and future earnings forecasts, though I acknowledge that analysis of the factors influencing the extent of consideration of each earnings component may be interesting. However, for completeness I do include discussion of robustness analysis which includes some control variables in section *D* of this chapter.

Results of the regressions using the "aggregate earnings specification" and "earnings components specification" appear in Panel A of Table 6, where they are estimated separately for forecasts of earnings 1-, 2-, 3-, and 4-quarters ahead (and annually in the 1-year ahead specification). These results indicate that earnings components better explain the future forecasts of analysts than aggregate earnings. Specifically, there is an R-square improvement of between 0.1186 and 0.1572, depending on the horizon. Vuong (1989) Z-tests confirm that these improvements are statistically significant at the one percent level.

To focus my analysis on the portion of analyst forecasts which contain information from the earnings announcement, I perform a complementary analysis which

[21] For this analysis only, *FORECAST* is multiplied by the ratio of shares to assets at the end of fiscal year *T* so that it is on the same scale as the dependent variables. For all analyses, *FORECAST, REVISION, and* $Surprise_T$ are winsorized at 1% and 99%.

isolates the revision portion of each forecast. $REVISION_{r,i,t+h}$ is calculated as the first forecast for analyst r for the quarter ending h quarters after time t following the earnings announcement of firm i for time t (*FORECAST*), minus the most recently-issued (prior to the earnings announcement) forecast by this analyst for quarter $t+h$ (*OLDFORECAST*). That is,

$$REVISION_{r,i,t+h} = FORECAST_{r,i,t+h} - OLDFORECAST_{r,i,t+h} \quad (7)$$

Additionally, $REVISION_{r,i,t+h}$ is scaled by the CRSP stock price at the end of the month preceding the month in which each analyst's *OLDFORECAST* was made. Corrections are made for any stock splits between the forecasts by multiplying the "new" forecast by the ratio of the "old" split adjustment factor (from CRSP) to the "new" split adjustment factor.

To examine whether the information from the components appears to be incorporated by analysts in the revised portion of their forecasts, I estimate a cross-sectional regression of the *REVISION* on the extent of *DCI*:

$$REVISION_{r,i,T+h} = \alpha_1 + \rho_1 RankSDCI_{i,T} + \phi_1 Surprise_{r,i,T} + \varepsilon_{r,i,T+h} \quad (8)$$

and

$$\left|REVISION_{r,i,T+h}\right| = \alpha_2 + \rho_2 RankDCI_{i,T} + \phi_2 \left|Surprise_{r,i,T}\right| + \varepsilon_{r,i,T+h} \quad (9)$$

where *RankSDCI* (*RankDCI*) is the annual decile-ranking of the *SDCI* (*DCI*) variable.[22] In Equation (8), a positive and significant value of ρ_1 indicates that the revision is higher (more positive or less negative) for analyst estimates of firm-years in which the components indicate higher persistence of earnings. In Equation (9), a positive and a

[22] Decile rankings are formed annually between one and ten; I then subtract one and divide the difference by nine, so that the *Rank* variables range between zero and one.

significant value of ρ_2 indicates that the *extent of revision* is greater for analyst estimates of firm-years in which the components indicate differential information about the performance of the firm than aggregate earnings does. $SURPRISE_{r,i,T}$, the difference between actual earnings in period *T* and the analyst's individual forecast prior to the earnings announcement, is used as a control variable as it would also influence the (extent of) analyst forecast revision.[23]

To provide an interpretation for these results, I discuss the following example. Firm A has relatively more income concentrated in low-persistence components, *RankDCI* (*RankSDCI*) is high (low). In this case, a positive coefficient on *RankSDCI* in equation (8) would indicate that the forecast will be revised downward and a positive coefficient on *RankDCI* in equation (9) indicate that the extent of this forecast revision will be greater than a firm with low *RankDCI*. Firm B has relatively more income concentrated in high-persistence components, so *RankDCI* and *RankSDCI* are both high. In this case, positive coefficients would indicate that the forecast for Firm B will be revised upward and the extent of this forecast will be greater than a firm with low *RankDCI*.

When estimating these two specifications as shown in panel B of table 6, the coefficients on S*DCI* and *DCI* are positive and significant, controlling for the earnings surprise. Thus, the (extent of) revision is increasing in directional (extent of) information in the earnings components relative to aggregate earnings. To quantify the economic

[23] $SURPRISE_{r,i,T}$ is anticipated to be highly predictive for the extent of analysts' revisions of future earnings (see Table 4 of Clement, Hales, and Xue (2008), for example). Alternative specifications of (8) and (9) eliminating the need for *Surprise* would be to replace *REVISION* with *FORECAST* as the independent variable. However, the benefit of using *REVISION* is that I can attempt to restrict the extent to which the forecast is revised based on information other than earnings announcement.

significance of the result for the equation (8) specification, a standard deviation increase in $SURPRISE_t$ (.0068) increases revision by 0.148% of market value, while a change from the bottom to top decile of $DCI^{+/-}$ increases the revision by 0.034% of market value. The relative magnitudes of the effects of a standard deviation increase in $|SURPRISE_t|$ and a change from the bottom to top decile of *DCI* are similar.

6.B. ARE FORECAST ERRORS ASSOCIATED WITH THE INFORMATION FROM COMPONENTS?

Tests in the previous subsection examine *whether* analysts use information in the components when predicting future earnings. In this subsection, I examine the extent of incorporation. I adapt a research design from Bradshaw et al. (2001), who show that analysts' forecast accuracy is decreasing in the level of accruals by sorting firm-years into accrual portfolios and regressing forecast accuracy on the accrual rank.[24] I test whether analyst forecast errors are increasing in the differential component information (*DCI*) by sorting firm-years into deciles based on this measure (*DCI*). I then estimate the following regression in aggregate and separately for each forecast horizon [$h \in (1, 4$ quarters)]:

$$\left|FERROR_{r,i,T+h}\right| = \alpha + \beta_1 RankDCI_{i,T} + \varepsilon_{r,i,T+h} \tag{10}$$

[24] Although the research design in this study is similar to Bradshaw et al. (2001), there are several differences. For example, they do not center their data around a prior-period earnings announcement and they use I/B/E/S monthly median *annual* forecasts rather than individual analyst *quarterly* forecasts. Also, their independent variable is signed forecast error (analyst optimism or "bias"), while I use focus on absolute forecast errors in this study.

where |*FERROR*| is the absolute value of the difference between a firm's actual earnings and the analyst's forecast.[25] A positive and significant β_1 coefficient indicates that the average analyst forecast error is greater for firm-years in which earnings components indicate differential information about the performance of the firm relative to aggregate earnings.

Results are presented in Table 7. Analysts' absolute forecast error, though not monotonic, is increasing (based on both means and medians) in the decile ranking of *DCI*, indicating that when there is a larger difference in the differential components information—when components tell a different story than aggregate earnings—analysts' forecast errors are greater (quarterly forecast errors tabulated only, see panel A). This is confirmed statistically with regression analysis, the results of which are presented in Panel B. Regardless of horizon, the coefficient on *RankDCI* is positive and significant. Thus, analysts' absolute forecast error is increasing in the decile ranking of *DCI*, indicating that when there is a larger difference in the differential components information—when components tell a different story than aggregate earnings—analysts' forecast errors are greater. Economically, a change from the bottom to top decile ranking of *DCI* is associated with an increase in the absolute forecast error of 0.00230, which is greater than the median analyst absolute forecast error (0.00196, untabulated). Thus, *DCI* is significantly associated with forecast errors, both statistically and economically.

---

[25] |*FERROR*| is adjusted by multiplying by the fraction of the split adjustment factor at the time of the earnings announcement (from CRSP) to the factor at the time of the forecast. It is also winsorized at the 99th percentile.

As I acknowledge, this estimation follows the research design of Bradshaw et al. (2001, table 5) for detecting whether forecasts errors are greater based on the independent variable. Although I do not initially anticipate a correlation between *RankDCI* and a variable used in their regressions (which measure the portfolio-ranking of working capital accruals), I estimate a specification which includes a similar variable to ensure I am not simply replicating their result with this analysis (untabulated). Inferences are unchanged. Further, when estimating the one-quarter ahead specification, the sign on the decile ranking of accruals is negative. This evidence suggests analysts have *lower* forecast errors for high accrual firms, but only for short-window (first quarter) forecasts, perhaps because they unwind a fourth-quarter affect.

The preceding test assumes all information (good or bad) is treated similarly by analysts, as forecast errors are modeled as a function of the extent of differential component information regardless of sign. As a further test which allows for the possibility that this information may be treated differently depending on whether the components indicate more or less persistence of earnings, I add to equation (10) the decile ranking of the signed variable, *SDCI* and re-estimate the regression. Controlling for the effect of the absolute difference between the predictions using aggregate earnings and earnings components, the coefficient on the signed variable illustrates the effect of the direction of the difference on analysts' forecast errors. Results, presented in table 7, panel C suggest that controlling for the absolute difference in the information from the components, earnings components that indicate more persistence than aggregate earnings are associated with lower analysts' forecast error, and, interestingly, when a firm's earnings components indicate less persistence than its aggregate earnings, analysts' forecast errors are higher.

To interpret these results, I once again consider example firms A and B. Firm A (B) has relatively more income concentrated in low-persistence (high-persistence) components, *RankDCI* is high (high) and *RankSDCI* is low (high). The coefficients in Panel B indicate that analyst forecast errors for firm A will be greater than for the average firm. However, for firm B, coefficients on the two variables are in offsetting directions, indicating that analyst forecast errors will be lower than for firm A. This means that although analysts incompletely utilize the information in earnings components, they do a better job incorporating it when the information suggests more persistent earnings (relative to aggregate earnings).

6.C. ARE FORECAST ERRORS ASSOCIATED WITH THE IMPROVEMENT FROM THE COMPONENT MODEL?

The above tests show that forecast errors are increasing in the differential component information, but do not address whether the component information *could have* been used to increase forecast accuracy. In other words, although I document a relation between absolute forecast errors and the extent of difference between the component and aggregate earnings models, these results do not imply that the error is increasing in the actual improvement of the components model. To address this related question, I examine whether the ex-post realized improvement from using the earnings components model is associated with analysts' error by estimating the following regression:

$$\left|FERROR_{i,T+h}\right| = \alpha + \beta_1 IMPROVEMENT_{i,T} + \varepsilon_{i,T+h} \tag{11}$$

where *IMPROVEMENT* is the ex-post realized improvement from using the components to predict future earnings relative to aggregate earnings, defined as | *Actual EARNINGS*$_{T+1}$ $- \widehat{EARNINGS}_{T+1\ INC}$ | − |*Actual EARNINGS*$_{t+1}$ $- \widehat{EARNINGS}_{T+1\ COMP}$ |.[26] By definition, when this value is higher, there is more accuracy to be gained by using the components relative to aggregate earnings when forecasting. I interpret a positive (negative) β_1 coefficient as indicating that analysts ignore (utilize) the valuable information from the components. Because of the previous result (that analysts appear to have a larger error when the components indicate less persistence), I separately analyze forecast errors of firm-years where the components indicate less persistence than aggregate earnings (*SDCI*<0) and where the components indicate more persistence than aggregate earnings (*SDCI*>0).

Results are reported in table 8. On average, I find that analysts' absolute forecast error is increasing in the improvement from components model when components indicate lower persistence than the aggregate earnings model (see panel A). That is, when components indicate less persistence, analysts seem to ignore this information (and by doing so, obtain a higher forecast error). Regardless of horizon, the coefficient on *IMPROVEMENT* is positive and significant.

[26] Using the decile ranking of *IMPROVEMENT* leads to similar inferences, but the interpretation is more comprehensive when using continuous values. It should also be noted that because of absolute values, *Actual EARNINGS* does not cancel out and this measure is quite different than *DCI*, even though they appear similar as constructed. *DCI* measures the difference in the predictions from one another, while *IMPROVEMENT* measures the difference in accuracy between the predictiosn.

On the other hand, when components indicate higher persistence (table 8, panel B), analysts appear to adequately incorporate the information from earnings components to reduce their forecast error, as the coefficient on *IMPROVEMENT* is negative and significant in each horizon. Combined, these two panels are consistent, and slightly more revealing, than the results presented in panel C of table 7. They appear to indicate that analysts are selective in their incorporation of information from earnings components depending on whether the components indicate that earnings is more persistent or less persistent than indicated by a simpler analysis of aggregate earnings.

The pattern of these results across horizons is also interesting. When components indicate lower persistence than aggregate earnings, the positive coefficient is greater for shorter horizons than longer horizons (0.01973 and 0.00993 for one-quarter ahead and four-quarters ahead, respectively). So, for one-quarter-ahead (four-quarter-ahead) forecasts, each dollar per asset improvement in the components model is associated with approximately four cents (two cents) of *additional* forecast error.[27] However, when components indicate more persistence, the relation between error and improvement is decreasing in horizon (-0.00662 and -0.03648 for one-quarter ahead and four-quarters ahead, respectively). So, for one-quarter (four-quarter) ahead forecasts, each dollar per asset improvement in the components model is associated with approximately one cents (seven cents) of *reduced* forecast error.

[27] This assumes price/assets of two, which is approximately equal to the sample average. (e.g. 0.01995*2≈$.04).

6.D. Discussion and Takeaways

A potential concern when interpreting the results in this section is that the sample of observations for the analyses are only aggregated at the individual firm-analyst-forecast level. That is, for each firm-fiscal year-end earnings announcement, there are potentially several forecast and revision observations because every analyst could forecast for each of four quarters, and a firm may potentially have several analysts. Although each forecast and revision will be different from the others, the observations may not be independent. Below I discuss four steps taken to remedy concerns about lack of independence between observations.

First, the tabulated results are in most cases reported *by quarter*. To the extent an analyst makes a similar revision for each quarter-ahead, grouping these observations together could reduce the standard errors and cause incorrect inferences. Estimating the regressions by quarter eliminates this particular concern. Second, in untabulated analysis I find that inferences based on test statistics computed using Rogers (1993) robust standard errors are identical to those reported in this section.[28] Third, in untabulated analysis I replace the individual analysts' revisions and forecast errors with the average revision and forecast error for each firm-year level observation. With this sample, I find qualitatively similar results. Fourth, I estimate all the analyses using annual regressions for each of the fourteen years in the sample period. Using the adjusted test statistic from these annual regression as described by Fama and MacBeth (1973), inferences are

[28] Specifically, I estimate each of the regressions reported in this chapter using a methodology that corrects the standard errors for dependence within a cluster of related observations. I consider both the firm and analyst as clusters which could potentially impair independence.

similar.[29] Overall, no evidence indicates that lack of independence between the observations causes any bias or improper inferences.

Another potential concern with the results in this section is that the variable of interest, which is intended to capture the extent to which earnings components have a weighted-average level of persistence that varies from the average firm, could instead be correlated with another variable that is already known to be associated with forecast errors. As discussed above, I adopt a methodology from Bradshaw et al. (2001) to test whether my main variable of interest (the decile ranking of *DCI*) is positively associated with absolute forecast errors. My main analysis has no control variables consistent with the methodology in Bradshaw et al. (2001).

A concern remains, however, that the positive association I document could be driven by the fact that firms with high *DCI* are simply harder to forecast (if such firms are indeed harder to forecast, which is not obvious).[30] To help alleviate this potential concern I look at the ex-post realized improvement from using the components model over the aggregate earnings model, and show that the improvement itself is positively associated with analyst forecast error. Also, in untabulated analysis, I augment equation (10) with several variable with may be associated with analyst forecast error. Below I discuss the construction of each control variable, the reason each are included, and the

---

[29] One exception is that when forecast error is regressed on improvement and *SDCI* is less than zero, the Fama-MacBeth t-statistic on *IMPROVEMENT* is only marginally significant in the two-quarter ahead horizon. When *SDCI* is greater than zero, it is insignificant at conventional levels in the one-quarter ahead and two-quarter ahead horizons. However, for all other individual quarter horizons, for "all quarters," and for the annual forecast errors, the adjusted t-statistic remains significant at the one percent level or better.

[30] As a counter-argument, consider a firm that has all permanent earnings and no transitory earnings. Because this differs from the average firm in its mix of earnings components, it would have a higher *DCI*. However, it may be easier to forecast the future earnings of this firm.

observed sign. When including these variables either individually or collectively, *RankDCI* remains positive and significant.

The following variables are considered (COMPUSTAT mnemonics in quotations and non-italicized capital letters, all at time *T*):

> *LOGSIZE* is the natural logarithm of total assets (COMPUSTAT=”AT”), and is included in the event smaller or larger firms are both harder to forecast and have a higher *DCI*. *LOGSIZE* is negatively associated with absolute forecast errors.
>
> *ROA* is income before discontinued operations (“IBA”), scaled by total assets (“AT”). It is included because more profitable firms may be easier to forecast. *ROA* is negatively associated with absolute forecast errors in three out of four horizons.
>
> *B/M* is book equity (“CEQ”) divided by market capitalization (“PRCC_F”*”CSHO”), and it included because high book-to-market firms may be distressed and more difficult to forecast. *B/M* is positively associated with absolute forecast errors.
>
> *SPIDUM* is an indicator variable equal to one if special items (“SPI”) is non-zero, or zero otherwise. *SPIDUM* is positively associated with absolute forecast errors in a univariate specification but is not statistically significant at conventional levels in the full specification (except marginally in the three-quarters ahead horizon).
>
> *DISP* is the dispersion (standard deviation) of analysts’ forecasts, which is set to zero in the event there is only one forecast. High dispersion may indicate that earnings is difficult to forecast. *DISP* is positively associated with absolute forecast errors.
>
> *AbsSURPRISE* is the absolute value of *SURPRISE*, the analyst’s own surprise, as previously defined. This is included because analysts’ errors may be serially correlated. It is positively associated with absolute forecast errors.
>
> *REVISION* is the analyst’s revision, as previously defined. It is included in the case that the extent of the revision of the forecast from its previous value is related to its accuracy. *REVISION* is negatively related to absolute forecast errors.

> *E/P* is actual earnings scaled by the stock price at the month prior to the earnings announcement. This may capture the extent to which earnings our transitory, which could be correlated with my variable of interest. *E/P* is negatively related to absolute forecast errors.

Because there are many specifications and there is no effect on *RankDCI*, I do not tabulate the results of this robustness test. However, in Table 9 I report the means and medians for each of the above variables for the full sample of revisions and separately for observations with the decile ranking of *DCI* between one and five and those with the decile ranking of *DCI* between six and ten.

Although evidence in this chapter indicates that the information about the persistence of earnings components is associated with analysts' forecast errors and that analysts' forecasts could be improved by incorporating information, the evidence does not imply that the earnings components model results in a prediction of earnings that is on average more accurate than analysts' forecasts.[31] Analysts have access to and incorporate substantial amounts of other financial and non-financial information into their forecasts, including industry and firm-specific information that is not included in the earnings components model.

The analyses in this chapter provide three primary inferences. First, information about the persistence of various earnings components is associated with analysts' forecasts and forecast revisions. Second, analysts' absolute forecast errors are increasing in the extent to which information from the components differs from information about aggregate earnings. This second result is weakened (magnified) when the components

[31] In fact, I examine this issue empirically and observe evidence to the contrary. In untabulated analysis using a sample of annual forecasts in which actual COMPUSTAT and IBES earnings per share are equal, I find that the absolute forecast errors from the earnings components model are greater than analysts' absolute forecast errors.

are more (less) persistent than the component mix of the average firm. Finally, I report that analysts appear to selectively incorporate information about the persistence of earnings components, depending on whether it indicates more or less persistence than aggregate earnings.

Chapter 7. Supplemental analyses: Earnings components through time

The final phase of this study examines the information content of earnings components through time. Dichev and Tang (2008) find that aggregate earnings is less persistent through time, which raises an empirical question about whether it would be more useful now for investors to consider future earnings a function of the persistence earnings components rather than a function of the persistence of aggregate earnings. I partition my forecasting sample into two time periods, the breakpoint of which is consistent with their study, 1970-1985 and 1986-2007 (subsequently referred to as the "early" and "recent" periods), to determine whether analysis of earnings components is more important for predicting earnings in the recent time period.

I then further partition a restricted subsample (which matches the timeline of my analyst forecast sample) into two equal time periods, 1994-2000 and 2001-2007 (subsequently referred to as "the nineties" and "the most recent period"). With this sample, I determine whether earnings components are more important for predicting earnings in the most recent time period.[32] Finally, I examine whether analysts' use of this information has changed through time.

I first compare the out-of-sample model forecast errors, which are differences of future earnings ($EARNINGS_{t+1}$) and predicted earnings using equations (1) and (2) for the early and recent time periods (equations (1) and (2) reflect the earnings components model and the aggregate earnings model, respectively). As reported in panel A of table

[32] As discussed above, Dichev and Tang (2008) use an earlier partition (pre-1986 and post-1985) to establish their inferences. However, the persistence of earnings continues to decline during the analyst sample period used in my study (1994-2006), allowing me to look at change in analyst incorporation of this information through time.

10, the aggregate earnings model has lower predictive ability in the recent period relative to the early period, as evidenced by the increased model forecast errors, from 0.0277 to 0.0639. Similarly, components are less predictive of future earnings in the recent period, as the forecast errors increase from 0.0267 to 0.0608. However, the improvement from the aggregate earnings to the components model more than triples from the early period (0.0010) to the recent period (0.0031), and this increase is statistically significant. This indicates that in the recent period it is more important to consider earnings components when predicting future earnings than in the early period.[33]

Turning to my second subsample (panel B of table 10), I repeat this analysis and find that the pattern is also present when comparing the nineties to the very recent period. That is, both the earnings components and aggregate earnings are less predictive of future earnings in the very recent period, but the earnings components model has improved on a relative basis (the improvement is 0.0027 on average in the nineties and 0.0049—almost double—in the very recent period). Thus, on a relative basis, it has continued to become even more beneficial to consider earnings components.

I next examine the association between earnings components and contemporaneous returns. Given the decrease in the persistence of aggregate earnings, I predict that, relative to the relation between current aggregate earnings and contemporaneous returns, the relation between the components of current earnings and contemporaneous returns has increased over time. I test this conjecture by estimating a

[33] One potential explanation might be that the recent time period has more earning volatility, or that accounting did a better job of controlling extreme observations in the earlier time period. However, in untabulated analysis I find that inferences are similar when the top and bottom 5% (annually) of $EARNINGS_{t+1}$, $\widehat{EARNINGS}_{T+1\,INC}$, and $\widehat{EARNINGS}_{T+1\,COMP}$ are removed.

regression of size-adjusted contemporaneous returns (*EARNRET*) on earnings surprises from each of the earnings components model and the aggregate earnings model, augmenting the regression with an intercept and slope coefficients for the *RECENT* period:

$$\begin{aligned}
&EARNRET_{T+1} = \beta_1 + \beta_2(EARNINGS_{T+1} - \widehat{EARNINGS_{T+1\,COMP}}) + \\
&\beta_3(EARNINGS_{T+1} - \widehat{EARNINGS_{T+1\,INC}}) + \beta_4 RECENT + \\
&\beta_5 RECENT * (EARNINGS_{T+1} - \widehat{EARNINGS_{T+1\,COMP}}) + \\
&\beta_6 RECENT * (EARNINGS_{T+1} - \widehat{EARNINGS_{T+1\,INC}})
\end{aligned} \tag{12}$$

Results are presented in panel A of table 11. Interestingly, in the early period, contemporaneous returns were largely a function of the surprise from the aggregate earnings model, with additional information from the surprise from the components associated with additional returns. However, in the recent period, returns are only a function of the surprise from the components, with no additional explanatory power from the surprise based on the aggregate earnings specification. Additionally, it should be noted that overall the earnings-return relation is substantially smaller in the recent period.

Using my restricted sample, I perform the same analysis and tabulate the results in panel B of table 11 (where the indicator variable *RECENT* in this panel used to indicate the most recent period). Inferences are somewhat different. In the nineties, contemporaneous returns were largely a function of the surprise from the components model. Controlling for the surprise from the earnings components model, the relation between size-adjusted returns and the earnings surprise from the aggregate earnings model was marginally significantly *negative*.[34] In the most recent period, returns are even more strongly related to the earnings surprise from the earnings components model. Thus, market participants appear to be responding even more strongly in the most recent period as if earnings components are considered when forming the expectations for earnings.

Finally, I conclude my study by examining whether analysts' use of information from earnings components has changed through time. I partition the sample using the time period used in the previous analyst forecast tests, on fiscal years ending before (or during) the year 2000 and those ending after 2000. I refer to these two sub-periods as "the nineties" and "the most recent period" as before. Augmenting equation (10), I estimate the following cross-sectional regression:

$$\left|FERROR_{i,T+h}\right| = \alpha + \beta_1 RankDCI_{i,T} + \beta_2 RECENT + \beta_3 RankDCI_{i,T} * RECENT + \varepsilon_{i,T+h} \quad (13)$$

where *RECENT* is an indicator variable set equal to one when the forecast is for fiscal years ending after 2000, and zero otherwise. A positive (negative) coefficient β_3 indicates that analyst forecast errors are more (less) associated with the extent of differential component information in the most recent period.

Results are presented in Table 12, and indicate a negative coefficient for the interaction between *RankDCI* and *RECENT* (β_3). This means that absolute analyst forecast errors are less associated with *RankDCI* in the most recent period, relative to the nineties. While the association between absolute error and *RankDCI* is still positive in

[34] While accurate, this inference must be properly understood due to the correlation between the two earnings surprises. The correlation between the size-adjusted returns earnings and the surprise from the aggregate earnings model is highly significantly positive, even in the nineties.

the recent period ($\beta_1 + \beta_3$=0.00217, F=191), analysts incorporate more information from the components into their forecasts in the recent period than in the nineties. This is consistent with analysts recognizing the increased importance of information from earnings components relative to aggregate earnings. Additionally, due to the overlap of the nineties vs. the most recent partition and Regulation FD, this evidence is also consistent with analysts engaging in more information discovery resulting from reduced access to management (Mohanram and Sunder 2006). Regardless of the rationale, analysts appear to more carefully identify the differential persistence of firms' earnings components in the most recent period, when it is more valuable relative to aggregate earnings for predicting future earnings.

Chapter 8. Conclusion

In this study, I provide evidence on the extent of investor and analyst incorporation of information from earnings components. Based on research indicating that the persistence of earnings has declined, it may be more important for investors and analysts to utilize information in earnings components. Also, few studies have provided evidence about whether analysts utilize the information provided by earnings components, and none have provided the direct evidence presented in this study. This study is timely as standard setters are considering amending the presentation and classification of earnings components in financial statements. It is also among the first to consider the change in the importance of earnings components through time for predicting future earnings and explaining returns.

In preliminary analyses, I utilize line items from the income statement and changes in accruals from the balance sheet to identify a broad set of earnings components which contain information (about persistence) predictive of future earnings. I examine the market's incorporation of this information by testing whether contemporaneous returns are more consistent with consideration of earnings components than aggregate earnings. I allow the estimated persistence of earnings components to change over time, and I find that my decomposition is better at predicting future earnings than information from aggregate earnings alone and less extensive dissagregations.[35] I also find that

[35] Instead, if a less comprehensive approach had been predictive as what I used in this study, even this would have warranted consideration by standard setters as they "address the presentation and display of financial statement information, including the classification and display of line items and the aggregation of line items into subtotals and totals." (FASB and IASB 2008).

earnings components are more consistent with the valuation of earnings surprises based on my analysis of contemporaneous returns.

My primary analyses investigate whether analysts fully incorporate information from earnings components. Previous studies have found predictable future returns based on information from earnings components. If analysts incorporate the information about the differential persistence of earnings components adequately into their forecasts, results from these studies would indicate that the market does not fully incorporate the information provided by analysts (consistent with post analyst-revision drift). Alternatively, if analysts do not fully incorporate this information, this would indicate that analysts contribute to this informational inefficiency (by making predictions consistent with the mispricing). My findings are more consistent with the latter alternative. That is, there appears to be information contained in the components that could be used to improve forecasts. This is especially true when a firm's income is concentrated in components with low persistence. These findings are informative to researchers because few studies have directly examined the components considered by analysts. They may also be helpful to investors who rely on analysts' earnings forecasts when making investment decisions.

Finally, I provide important evidence on the relation between earnings components and future earnings through time. Dichev and Tang (2008) conjecture that declining earnings persistence may have resulted from innovations in accounting standards. This may indicate that a greater role exists for earnings components in firm valuation, and standard setters are well-warranted to enhance the presentation and disclosure of financial statement classifications. Alternatively, if there has been no change in the information available to be gathered from earnings components or if their usefulness has declined along with the usefulness of the aggregate earnings measure, this may call into question the value relevance of the accounting framework which has developed over the past few decades. I report that the usefulness of components relative to aggregate earnings has increased dramatically. Interestingly, the usefulness of earnings components relative to aggregate earnings for predicting earnings and explaining returns has improved substantially not only over the past several decades, but even within the past fifteen years. Analysts appear to recognize that earnings components are more important at predicting future earnings because the positive relation between their errors and the information from earnings components has declined through time. These findings are not only useful to researchers, investors, and analysts, but could also be informative to financial statement preparers who may be concerned that analysts and investors focus too much on "the bottom line." My results suggest this is less true in recent years.

Future work based on the framework in this study could examine many issues. With respect to forecasting, a similar methodology may be useful to predict cash flows or explain price multiples. Analysts' use of components could also be further explored, for example when making recommendations and setting target prices. The "on average" effects presented in this dissertation could also be studied more carefully to discover whether certain analyst characteristics are associated with a greater extent of incorporation of the persistence information of the earnings components (if some analysts are better than others at incorporating information from the components). Finally, determining whether the intertemporal change in the persistence of various earnings components is associated with changes in particular accounting standards would also be informative to standard setters and financial statement users.

Figure 1: Five-year rolling estimation window for equations (1) and (2)

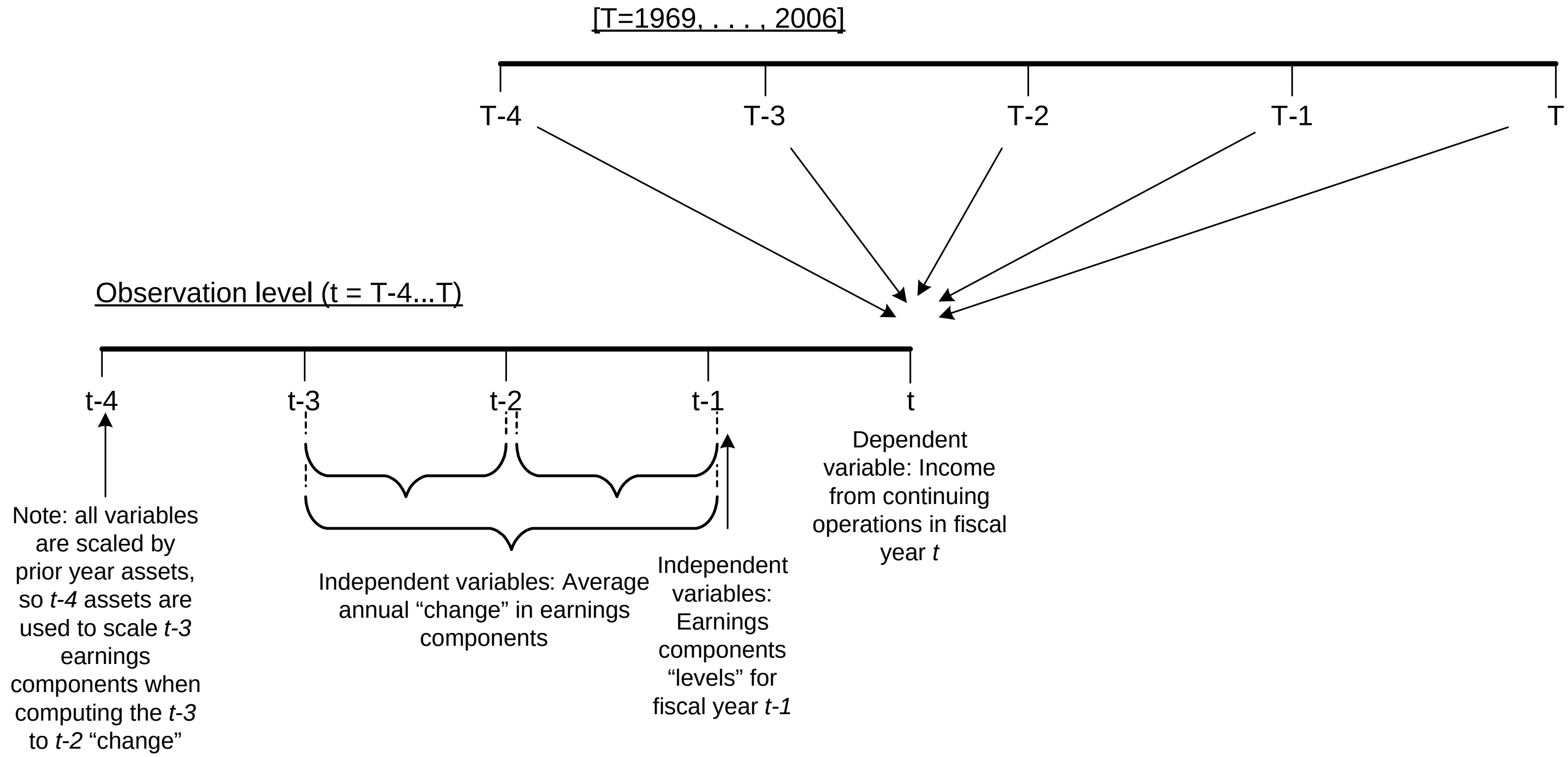

Figure 2: Estimation window for calculating analyst forecasts and returns

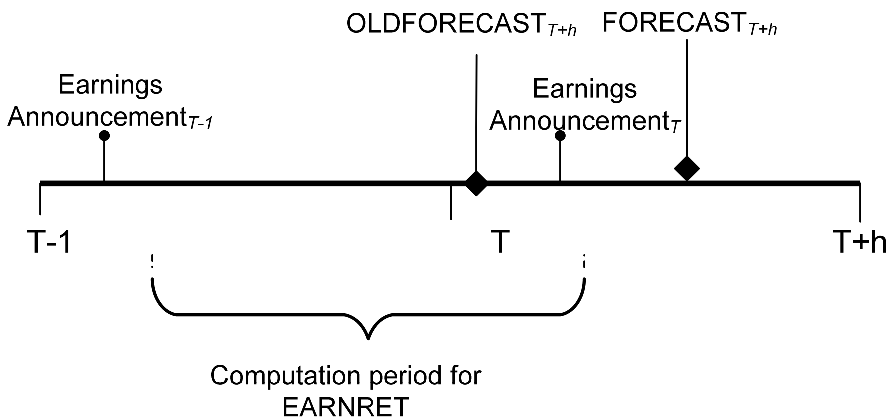

Table 1: Descriptive statistics

Panel A: Annual income statement components (/Lagged Assets)

Components (COMPUSTAT mnemonic):	Mean	25th Pctl	Median	75th Pctl
Income before extraordinary items (IB)	0.0267	0.0101	0.0421	0.0813
Sales (SALE)	1.2121	0.4173	1.0216	1.6589
Cost of goods sold (COGS)	0.8644	0.2385	0.6438	1.1720
Selling, general, and administrative (XSGA)	0.2218	0.0137	0.1388	0.3390
Depreciation and amortization (DP)	0.0445	0.0209	0.0377	0.0575
Interest expense (XINT)	0.0254	0.0048	0.0202	0.0358
Special Items (SPI)	-0.0075	0	0	0
Income taxes (TXT)	0.0319	0.0027	0.0208	0.0497
Minority interest (MII)	0.0006	0	0	0
Nonoperating income (NOPI)	0.0107	0	0.0054	0.0163

Panel B: "Cash" portion of annual income statement components (/Lagged Assets)

Cash portion of component:	Mean	25th Pctl	Median	75th Pctl
Cash received from customers	1.1839	0.4125	1.0068	1.6291
Cash paid for goods sold	0.8486	0.2359	0.6326	1.1502
Cash SG&A	0.2024	0.0024	0.1307	0.3283
Purchases of PP&E	0.0836	0.0137	0.0511	0.1060
Cash paid for interest	0.0254	0.0048	0.0202	0.0358
Cash paid for taxes	0.0278	0.0013	0.0159	0.0454
Cash paid for minority interest	-0.0007	0	0	0
Cash non-operating income	0.0046	-0.0165	0.0093	0.0376

Panel C: "Accrued" portion of annual income statement components (/Lagged Assets)

Accrued portion of component:	Mean	25th Pctl	Median	75th Pctl
Accrued sales	0.0282	-0.0040	0.0104	0.0448
Accrued cost of goods sold	0.0158	-0.0013	0.0003	0.0226
Accrued SG&A	0.0195	-0.0043	0.0059	0.0274
Depreciation	0.0445	0.0209	0.0377	0.0575
Change in debt	0.0362	-0.0187	0.0010	0.0575
Special items (assumes all accrued)	-0.0075	0	0	0
Change in deferred taxes	0.0041	0	0	0.0055
Change in minority interest	0.0013	0	0	0
Accrued non-operating income	0.0061	-0.0246	-0.0011	0.0232

Table 1, continued

Panel D: Average change in income statement components (/Lagged Assets)

Change in component:	Mean	25th Pctl	Median	75th Pctl
Income before extraordinary items	-0.0000	-0.0153	-0.0001	0.0122
Sales	-0.0281	-0.0850	-0.0009	0.0626
Cost of goods sold	-0.0172	-0.0562	-0.0004	0.0418
Selling, general, and administrative	-0.0085	-0.0096	0	0.0069
Depreciation and amortization	-0.0006	-0.0024	0	0.0025
Interest expense	-0.0006	-0.0027	0	0.0021
Special items	0.0001	0	0	0
Income taxes	-0.0017	-0.0071	0	0.0054
Minority interest	0	0	0	0
Nonoperating income	-0.0007	-0.0025	0	0.0021

Notes

N=167,670 for all panels, T=1969 to 2006.

This table reports descriptive statistics for the income statement components used in equation (1). See section chapter 4 for descriptions of each component.

Table 2: In-sample estimation details for equation (1) and (2)

Panel A: Average coefficients on level component (N=38)

Components (COMPUSTAT mnemonic)/Assets:	Cash Portion	Accrual Portion	Average Difference
Sales (SALE)	0.7263	0.7128	0.0135
Cost of goods sold (COGS)	-0.7267	-0.7826	0.0559
Selling, general, and administrative (XSGA)	-0.7279	-0.7295	0.0016
Depreciation and amortization (DP)[a]	-0.0260	-0.6592	-0.6331
Interest expense (XINT)[a]	-0.7405	-0.0179	-0.7226
Special Items (SPI)[b]	n/a	0.1789	n/a
Income taxes (TXT)	-0.4977	-0.5273	0.0296
Minority interest (MII)	-0.7577	-0.7365	-0.0212
Nonoperating income (NOPI)	0.5592	0.5476	0.0116

Panel B: Average coefficient on average changes component (N=38)

Components (COMPUSTAT mnemonic)/Assets:	Average Coefficient
Sales (SALE)	-0.0873
Cost of goods sold (COGS)	0.1048
Selling, general, and administrative (XSGA)	0.1040
Depreciation and amortization (DP)	0.1090
Interest expense (XINT)	0.0862
Special Items (SPI)	-0.0668
Income taxes (TXT)	0.1512
Minority interest (MII)	0.0116
Nonoperating income (NOPI)	-0.1370

Panel C: Average coefficients on terms in equation (2) (N=38)

Term (COMPUSTAT mnemonic)/Assets:	Average Coefficient
Profit (1 if IB>0, 0 otherwise)	0.0081
Earnings (IB)	0.4396
Profit × Earnings	0.3417
Average change in prior earnings	-0.0811

Table 2, continued

Panel D: Adjusted R-square from in-sample regressions (38 rolling 5 year windows)

Specification:	# IVs	Mean	25th Pctl	Median	75th Pctl
Aggregate Earnings (Eq. (2))	4	0.6630	0.6044	0.6378	0.7086
Earnings Components (Eq. (1))	23	0.7134	0.6636	0.6866	0.7571

Panel E: Predicted Earnings and Differential Components Information (N=167,670)[c]

	Mean	Std Dev.	25th Pctl	Median	75th Pctl
Predicted Earnings/Lagged Assets from:					
Aggregate Earnings (Eq. (2))	0.0315	0.1292	0.0140	0.0387	0.0692
Components (Eq. (1))	0.0308	0.1169	0.0124	0.0385	0.0709

	Mean	Min	25th Pctl	Median	75th Pctl	Max
Differential Components Information:						
DCI	0.2862	0.0000	0.0690	0.1598	0.3500	4.3976
SDCI	0.0739	-0.8894	-0.1338	0.0336	0.1797	4.3976

Notes

[a]Cash and accrual portions do not sum to the income statement component for these items. A simplifying assumption is made that the income statement portion is all cash (in the case of interest) or all non-cash (in the case of depreciation). However, the other portion is information easily obtained from the balance sheet and expected to directly affect future income through this income statement item.

[b]Special items is retained in aggregate for the analysis.

[c]When the two specifications resulted in *Predicted Earnings/Assets* which differed in sign, the observation was deleted (N=11,004).

Also, outliers for *DCI* (>99%) and *SDCI* (<1%/>99%) were trimmed (N=3,420), so the min and max represent the 0%/99% and 1%/99% for the full sample and N=167,670 refers to the number of observations in the remaining sample.

Table 3: Out-of-sample forecast errors

Table 3
Out-of-sample forecast errors

Average raw forecast errors	Mean	Std Dev.	25th Pctl	Median	75th Pctl
(a)Random walk of *Earnings/Assets*	-0.0027	0.2335	-0.0227	-0.0003	0.0161
(b)Eq. (2) [aggregate earnings model]	-0.0075	0.1796	-0.0184	0.0011	0.0214
(c)Eq. (1) [components model]	-0.0067	0.1639	-0.0181	0.0010	0.0194
(d)Fairfield et al. [Ops, Nonopt&tax]	-0.0076	0.1650	-0.0179	0.0021	0.0212
(e)Accruals & Cash Flows	-0.0075	0.1768	-0.0197	0.0014	0.0218

Average absolute forecast errors	Mean	Std Dev.	25th Pctl	Median	75th Pctl
(a)Random walk of *Earnings/Assets*	0.0564	0.2266	0.0058	0.0191	0.0531
(b)Eq. (2) [aggregate earnings model]	0.0522	0.1720	0.0072	0.0202	0.0506
(c)Eq. (1) [components model]	0.0497	0.1563	0.0067	0.0189	0.0481
(d)Fairfield et al. [Ops, Nonopt&tax]	0.0505	0.1573	0.0076	0.0199	0.0491
(e)Accruals & Cash Flows	0.0523	0.1691	0.0082	0.0209	0.0513

Average Improvement in absolute AFE relative to a random walk [by observation]

	Mean	t-statistic
Aggregate earnings [(a)-(b)]	0.0042	16.82
Components [(a)-(c)]	0.0066	19.25
Fairfield et al. [(a)-(d)]	0.0059	17.84
Accruals [(a)-(e)]	0.0040	16.14

Average Improvement in absolute AFE relative to the components model [by observation]

	Mean	t-statistic
Aggregate earnings [(b)-(c)]	0.0025	17.43
Fairfield et al. [(d)-(c)]	0.0008	12.82
Accruals [(e)-(c)]	0.0026	18.50

Notes
This table reports average raw and absolute average forecast errors from a random walk of Earnings/Assets, the aggregate earnings model (Equation 2), and the components model (Equation 1). For comparative purposes, it also reports the errors from two disaggregation models used in prior literature. The Fairfield et al. (1996) uses the following components: Operating income, non-operating income and tax, and special items. The accruals & cash flows model follows Collins and Hribar (2000). Further discussion of these models is in chapter 5. Earnings and components from all models are scaled by assets.

Table 4: Contemporaneous returns

Dependent Variable=	*Raw Return*		*Market-Adj Return*		*Size-Adj Return*	
	Coef	t-stat	Coef	t-stat	Coef	t-stat
Intercept	0.1636	73.43	0.0393	18.28	0.0091	4.24
News from aggregate earnings model	4.2311	53.67	4.1867	55.03	4.3503	56.93
Incremental news from components	3.6129	25.93	3.4988	26.02	3.6085	26.80
Large Surprise (Indicator variable)	0.0918	18.39	0.0893	18.52	0.0778	16.24
Large Surprise*News from aggregate	-3.7784	-47.35	-3.7379	-48.53	-3.9085	-50.55
Large Surprise*Inc. news from comp.	-3.1623	-21.84	-3.0616	-21.90	-3.1588	-22.60
N		121,767		121,767		117,774
R-square		0.036		0.037		0.040

Notes

This table reports results of a regression of contemporaneous returns (12 months ending at the end of the month of the earnings announcement) on earnings news, where earnings news is decomposed into two pieces: 1) the surprise based on actual GAAP earnings minus an earnings prediction based on Equation (2), and 2) the incremental surprise to an investor who used the components model rather than the aggregate earnings model.

Table 5: Firm characteristics and improvement

Panel A: Average firm characteristics

	IMPROVEMENT			
	Full sample	Below median	Above median	%diff.
Total assets ($millions)	2,873	2,956	2,790	-6%
Book/market	0.764	0.800	0.727	-9%
Return on assets	0.012	0.016	0.009	-45%
Special items indicator	0.342	0.338	0.346	2%
Growth in sales/assets	-0.027	-0.028	-0.027	-2%
Loss indicator	0.203	0.189	0.216	14%
Accruals	-0.041	-0.040	-0.042	6%

Panel B: Improvement by industry

		IMPROVEMENT	
	N	Mean	Median
Unassigned	1,635	0.0034	0.0005
Mining/Construction	5,413	0.0008	0.0005
Food	5,228	0.0022	0.0014
Textiles/Print/Publish	11,200	0.0021	0.0017
Chemicals	4,267	0.0022	0.0018
Pharmaceuticals	4,712	0.0151	0.0067
Extractive	7,228	0.0001	0.0003
Manf:Rubber/glass/etc	4,365	0.0031	0.0017
Manf:Metal	6,717	0.0048	0.0013
Manf:Machinery	5,762	0.0025	0.0016
Manf:ElectricalEqpt	6,283	0.0036	0.0019
Manf:TransportEqpt	4,024	0.0023	0.0017
Manf:Instruments	6,406	0.0041	0.0017
Manf:Misc.	1,602	0.0028	0.0012
Computers	12,861	0.0038	0.0019
Transportation	10,785	0.0043	0.0016
Utilities	12,066	0.0003	0.0002
Retail:Wholesale	6,472	0.0009	0.0006
Retail:Misc.	9,473	0.0014	0.0006
Retail:Restaurant	2,143	0.0030	0.0022
Financial	20,204	0.0005	0.0002
Insurance/RealEstate	7,698	0.0006	-0.0004
Services	11,126	0.0024	0.0012

Notes

IMPROVEMENT refers to the reduction in absolute forecast error provided by the earnings components model (based on equation (1)) compared to the aggregate earnings model based on equation (2), scaled by assets. Firm characteristics are defined in chapter 5.

Table 6: Analysts' use of components

Panel A: Comparison of regressions of analyst forecasts on earnings vs. components

	Horizon (# quarters ahead)				
	1	2	3	4	Annual
Aggregate Earnings Specification:					

$$FORECAST_{r,i,t+h} = \alpha_1 + \alpha_2 EARNINGS_{i,t} + \alpha_3 PROFIT_{i,t} + \alpha_4 PROFIT_{i,t} * EARNINGS_{i,t} + \alpha_5 AVG\Delta EARNINGS_{i,t} + \varepsilon_{i,t+h}$$

	1	2	3	4	Annual
R-square	0.5434	0.5132	0.4928	0.4631	0.5713

Earnings Components Specification:

$$FORECAST_{r,i,t+h} = \alpha_1 + \sum_{j=1}^{n+1} \alpha_j CC_{i,j,t} + \sum_{k=n+2}^{n+p+1} \alpha_k ACC_{i,k,t} + \sum_{l=n+p+2}^{2n+p+1} \alpha_l AVG\Delta ISC_{i,l,t} + \varepsilon_{i,t+h}$$

	1	2	3	4	Annual
R-square	0.6620	0.6536	0.6330	0.6203	0.7104
N	53,019	49,181	48,370	51,017	109,007
Difference in R-Square	0.1186	0.1403	0.1402	0.1572	0.1391
Vuong Z-test	16.70	15.33	11.39	12.62	21.95

Panel B: Regression of forecast revisions on information from components

$$REVISION_{r,i,T+h} = \alpha + \rho RankSDCI_{i,T} + \phi Surprise_{r,i,T} + \varepsilon_{r,i,T+h}$$

	Coefficient sig.		
Intercept	-0.00125***		
RankSDCI	0.00034***	R-square	0.0922
Surprise$_T$	0.21783***	N	201,587

$$\left|REVISION_{r,i,T+h}\right| = \alpha + \rho RankDCI_{i,T} + \left|\phi Surprise_{r,i,T}\right| + \varepsilon_{r,i,T+h}$$

	Coefficient sig.		
Intercept	0.00148***		
RankDCI	0.00078***	R-Square	0.0734
|*Surprise$_T$*|	0.44333***	N	201,587

Notes:
FORECAST (REVISION) is the analyst's first quarterly forecast (revision) made following the fourth quarter earnings announcement. The independent variables in Panel A are based on those in equations (1) and (2). RankDCI is the annual decile ranking of the differential component information measures as defined in equations (3). Surprise is the analyst forecast error for analyst *r* in the fourth quarter of the prior year. *** indicates significance at the 1% level.

Table 7: Analyst forecast errors and DCI

Panel A: Absolute forecast error by decile rank of *DCI* (all quarters)

	N	Mean	Stddev	Median
Decile 1 (*RankDCI*=0)	20,078	0.00465	0.00871	0.00172
Decile 2	20,100	0.00472	0.00822	0.00187
Decile 3	20,217	0.00443	0.00784	0.00178
Decile 4	20,087	0.00482	0.00895	0.00169
Decile 5	20,142	0.00462	0.00807	0.00181
Decile 6	20,181	0.00514	0.00994	0.00173
Decile 7	20,221	0.00567	0.01009	0.00207
Decile 8	20,327	0.00570	0.01034	0.00214
Decile 9	19,933	0.00633	0.01094	0.00230
Decile 10 (*RankDCI*=1)	20,301	0.00703	0.01135	0.00288

Panel B: Regression of absolute forecast error on decile rank of *DCI**

$$\left| FERROR_{r,i,T+h} \right| = \alpha + \beta_1 RankDCI_{i,T} + \varepsilon_{r,i,T+h}$$

	N	*RankDCI*	t-statistic
All Quarters	201,587	0.00230	34.57
1-Qtr Ahead	53,019	0.00160	17.24
2-Qtrs Ahead	49,181	0.00228	18.55
3-Qtrs Ahead	48,370	0.00257	17.71
4-Qtrs Ahead	51,017	0.00288	18.19
Annual (1-yr. Ahead)	109,007	0.01092	33.70

Table 7, continued

Panel C: Regression of absolute forecast error on decile of *DCI* and *SDCI**

$$\left|FERROR_{r,i,T+h}\right| = \alpha + \beta_1 RankDCI_{i,T} + \beta_2 RankSDCI_{i,T} + \varepsilon_{r,i,T+h}$$

	N	*RankDCI*	t-statistic	*RankSDCI*	t-static
All Quarters	201,587	0.00246	36.95	-0.00176	-26.45
1-Qtr Ahead	53,019	0.00176	18.81	-0.00152	-16.30
2-Qtrs Ahead	49,181	0.00240	19.48	-0.00137	-11.13
3-Qtrs Ahead	48,370	0.00274	18.86	-0.00190	-13.04
4-Qtrs Ahead	51,017	0.00310	19.55	-0.00235	-14.81
Annual (1-yr. Ahead)	109,007	0.01214	37.10	-0.00789	-24.12

Notes:
*An intercept is included but not tabulated. *FERROR* is the analyst's forecast error from the first quarterly forecast made following the fourth quarter earnings announcement from the prior fiscal year. RankDCI and RankSDCI are annual decile rankings of the differential component information measures as defined in equations (3) and (4), respectively.

Table 8: Improvement from components

$$\left| FERROR_{i,T+h} \right| = \alpha + \beta_1 IMPROVEMENT_{i,T} + \varepsilon_{i,T+h}$$

Panel A: SDCI < 0

	N	*IMPROVEMENT*	t-statistic
All Quarters	84,369	0.01259	20.82
1-Qtr Ahead	22,121	0.01973	21.94
2-Qtrs Ahead	20,794	0.01092	10.16
3-Qtrs Ahead	20,326	0.00949	7.35
4-Qtrs Ahead	21,128	0.00993	6.74
Annual (1-yr. Ahead)	42,932	0.03273	9.33

Panel B: SDCI > 0

	N	*IMPROVEMENT*	t-statistic
All Quarters	117,218	-0.01980	-21.51
1-Qtr Ahead	30,898	-0.00662	-5.44
2-Qtrs Ahead	28,387	-0.01229	-7.05
3-Qtrs Ahead	28,044	-0.02484	-12.49
4-Qtrs Ahead	29,889	-0.03648	-16.61
Annual (1-yr. Ahead)	66,075	-0.08248	-18.25

Notes:
*An intercept is included but not tabulated. *FERROR* is the analyst's forecast error from the first quarterly forecast made following the fourth quarter earnings announcement from the prior fiscal year. *IMPROVEMENT* is the ex-post realized improvement for the next fiscal year based on the prediction of the components model (equation (1)) relative to the aggregate earnings model (equation (2)). SDCI is the signed differential component information measure as defined in equation (4).

Table 9: Firm-forecast characteristics and DCI

Average firm-analyst-forecast characteristics		*Decile of DCI*		
	Full Sample	one to five	six to ten	%diff.
Log(total assets)	7.5374	7.4755	7.5992	1.7%
Book/market ratio	0.4093	0.3886	0.4299	10.6%
Return on assets	0.0359	0.0513	0.0206	-59.8%
Special items indicator	0.6124	0.5531	0.6715	21.4%
Dispersion	0.0317	0.0294	0.0340	15.7%
Abs(Surprise)	0.0033	0.0030	0.0037	24.7%
Revision	-0.0008	-0.0007	-0.0010	38.8%
E/P ratio	0.0099	0.0105	0.0093	-11.7%

Notes
DCI is the differential component information measure defined in equation (3). The firm and forecast characteristics are defined in chapter 6. Continous non-logged and non-ranked variables have been winsorized at the first and 99th percentile.

Table 10: Out of sample forecast errors of predictive models through time

Panel A: 1970-1985 vs. 1986-2007

Model forecast error	Average Pre-1986	Average Post-1985	Difference	t-statistic
$\left\| EARNINGS_{T+1} - \widehat{EARNINGS}_{T+1\,INC} \right\|$	0.0277	0.0639	0.0363	56.46
$\left\| EARNINGS_{T+1} - \widehat{EARNINGS}_{T+1\,COMP} \right\|$	0.0267	0.0608	0.0341	58.18
Improvement(Components model)	0.0010	0.0031		
t-statistic	17.25	15.23		
% of time Improvement > 0.01	13%	23%		
Change in Improvement from Pre to Post			**0.0021**	**9.90**

Panel B: 1994-2000 vs. 2001-2007

Model forecast error	Average Pre-2001	Average Post-2000	Difference	t-statistic
$\left\| EARNINGS_{T+1} - \widehat{EARNINGS}_{T+1\,INC} \right\|$	0.0668	0.0761	0.0093	5.62
$\left\| EARNINGS_{T+1} - \widehat{EARNINGS}_{T+1\,COMP} \right\|$	0.0641	0.0712	0.0071	4.80
Improvement(Components model)	0.0027	0.0049		
t-statistic	14.76	8.95		
% of time Improvement > 0.01	23%	27%		
Change in Improvement from Pre to Post			**0.0022**	**3.74**

Notes:
This table reports differences in out-of-sample forecast errors based on the aggregate earnings model (equation 2) and the earnings components model (equation 1).

Table 11: Contemporaneous returns through time

Panel A: 1970-1985 vs. 1986-2007

Variable	Coef	t-stat	*RECENT* Sum	Pr > F
Intercept	0.0263	7.96		
$\left\|EARNINGS_{T+1} - \widehat{EARNINGS}_{T+1\,INC}\right\|$	2.6393	10.87		
$\left\|EARNINGS_{T+1} - \widehat{EARNINGS}_{T+1\,COMP}\right\|$	0.9132	3.66		
RECENT	0.0025	0.60	0.0287	<.0001
*RECENT** $\left\|EARNINGS_{T+1} - \widehat{EARNINGS}_{T+1\,INC}\right\|$	-2.6420	-10.78	-0.0027	0.936
*RECENT** $\left\|EARNINGS_{T+1} - \widehat{EARNINGS}_{T+1\,COMP}\right\|$	-0.4868	-1.93	0.4264	<.0001
R-Square	0.034			
N	117,780			

Panel B: 1994-2000 vs. 2001-2007

Variable	Coef	t-stat	*RECENT* Sum	Pr > F
Intercept	0.0136	2.76		
$\left\|EARNINGS_{T+1} - \widehat{EARNINGS}_{T+1\,INC}\right\|$	-0.2145	-1.65		
$\left\|EARNINGS_{T+1} - \widehat{EARNINGS}_{T+1\,COMP}\right\|$	0.4453	3.39		
RECENT	0.0397	5.52	0.0533	<.0001
*RECENT** $\left\|EARNINGS_{T+1} - \widehat{EARNINGS}_{T+1\,INC}\right\|$	0.1299	0.94	-0.0846	0.067
*RECENT** $\left\|EARNINGS_{T+1} - \widehat{EARNINGS}_{T+1\,COMP}\right\|$	0.2716	1.89	0.7169	<.0001
R-Square	0.012			
N	53,971			

Notes

This table presents cross-sectional regression results of size-adjusted contemporaneous returns regressed on earnings surprises from each of the earnings components and aggregate earnings model, with slope and interecept coefficients for the recent and most recent time periods, as defined in chapter 7.

Table 12: Analysts' forecast errors through time

$$\left|FERROR_{i,T+h}\right| = \alpha + \beta_1 RankDCI_{i,T} + \beta_2 RECENT + \beta_3 RankDCI_{i,T} * RECENT + \varepsilon_{i,T+h}$$

	All Quarters		1-Qtr Ahead		2-Qtrs Ahead		3-Qtrs Ahead		4-Qtrs Ahead	
Variable	Coef.	t-statistic	Coef.	t-statistic	Coef.	t-statistic	Coef.	t-statistic	Coef.	t-statistic
Intercept	0.00348	23.05	0.00191	12.60	0.00284	10.13	0.0041	13.60	0.00532	12.44
RankDCI	0.00538	21.11	0.00288	11.30	0.00508	10.80	0.0059	11.45	0.00839	11.57
RECENT	0.00127	7.13	0.00086	4.78	0.00114	3.46	0.0013	3.61	0.00144	2.91
*RankDCI*RECENT*	-0.00321	-10.73	-0.00144	-4.73	-0.00267	-4.82	-0.0034	-5.71	-0.00590	-7.01

	Annual (1-Yr. Ahead)	
Variable	Coef.	t-statistic
Intercept	0.01269	40.98
RankDCI	0.01583	30.39
RECENT	0.00214	5.42
*RankDCI*RECENT*	-0.00801	-12.05

Notes:

Panel A reports differences in out-of-sample forecast errors based on the aggregate earnings model (equation 2) and the earnings components model (equation 1). In Panel B, *FERROR* and *RANKDCI* are defined in Table 5. *RECENT* is an indicator variable equal to one if the forecasted period is in 2001 or later, zero otherwise.

References

Abarbanell, J. S. and B. J. Bushee. 1997. Fundamental analysis, future earnings, and stock prices. *Journal of Accounting Research* 35 (Spring): 1-24.

-----. 1998. Abnormal returns to a fundamental analysis strategy. *The Accounting Review* 73 (January): 19-45.

Ali, A., A. Klein, and J. Rosenfeld. 1992. Analysts' use of information about permanent and transitory earnings components in forecasting annual EPS. *The Accounting Review* 67 (January): 183-198.

Banker, R. D. and L. Chen. 2006. Predicting earnings using a model based on cost variability and cost stickiness. *Accounting Review* 81 (March): 285-307.

Barth, M. E., W. H. Beaver, J. R. M. Hand, and W. R. Landsman. 1999. Accruals, cash flows, and equity values. *Review of Accounting Studies* 4 (December): 205-229.

Barth, M. E., D. P. Cram, and K. K. Nelson. 2001. Accruals and the prediction of future cash flows. *The Accounting Review* 76 (January): 27-58.

Belsley, D. A. 1984. Collinearity and forecasting. *Journal of Forecasting* 3 (April/June): 183-196.

Bhattacharya, N., E. L. Black, T. E. Christensen, and C. R. Larson. 2003. Assessing the relative informativeness and permanence of pro forma earnings and GAAP operating earnings. *Journal of Accounting and Economics* 36 (December): 285-319.

Boyd, D. T., L. Kronk, and R. Skinner. 2002. The effects of just-in-time systems on financial accounting metrics. *Industrial Management & Data Systems* 102: 153-164.

Bradshaw, M. T., S. A. Richardson, and R. G. Sloan. 2001. Do analysts and auditors use information in accruals? *Journal of Accounting Research* 39 (June): 45-74.

Brown, L. D. and K. Sivakumar. 2003. Comparing the value relevance of two operating income measures. *Review of Accounting Studies* 8 (December): 561-572.

Call, A. C., S. Chen, and Y. H. Tong. 2008. *Disaggregation vs. Aggregation: Are earnings forecasts accompanied by cash flow forecasts more accurate?* Working Paper*:* University of Georgia.

Chandra, U. and B. T. Ro. 2008. The role of revenue in firm valuation. *Accounting Horizons* 22 (June): 199-222.

Clement, M. B., J. Hales, and Y. Xue. 2008. *Understanding analysts' use and under-use of stock returns and other analysts' forecasts when forecasting earnings.* Working Paper*:* University of Texas at Austin.

Collins, D. W. and S. P. Kothari. 1989. An analysis of intertemporal and cross-sectional determinants of earnings response coefficients. *Journal of Accounting and Economics* 11 (July): 143-181.

Collins, D. W., E. L. Maydew, and I. S. Weiss. 1997. Changes in the value-relevance of earnings and book values over the past forty years. *Journal of Accounting and Economics* 24 (December): 39-67.

Collins, D. W. and P. Hribar. 2000. Earning-based and accrual-based market anomalies: One effect or two? *Journal of Accounting & Economics* 29 (February): 101-123.

Dechow, P. and W. Ge. 2006. The persistence of earnings and cash flows and the role of special items: Implications for the accrual anomaly. *Review of Accounting Studies* 11 (September): 253-296.

Dichev, I. D. and V. W. Tang. 2008. Matching and the changing properties of accounting earnings over the last 40 years. *The Accounting Review* 83 (November): 1425-1460.

-----. 2009. Earnings volatility and earnings predictability. *Journal of Accounting and Economics* 47 (March): 160-181.

Doyle, J. T., R. J. Lundholm, and M. T. Soliman. 2003. The predictive value of expenses excluded from pro forma earnings. *Review of Accounting Studies* 8 (June): 145-174.

Easton, P. 1998. Discussion: "Valuation of permanent, transitory, and price-irrelevant components of reported earnings". *Journal of Accounting, Auditing & Finance* 13 (Summer): 337-349.

Easton, P. D. and T. S. Harris. 1991. Earnings as an explanatory variable for returns. *Journal of Accounting Research* 29 (Spring): 19-36.

Ertimur, Y., J. Livnat, and M. Martikainen. 2003. Differential market reactions to revenue and expense surprises. *Review of Accounting Studies* 8 (June): 185-211.

Ertimur, Y., W. J. Mayew, and S. R. Stubben. 2008. *Analyst reputation and the issuance of disaggregated earnings forecasts to I/B/E/S.* Working Paper*:* Duke University.

Fairfield, P. M., R. J. Sweeney, and T. L. Yohn. 1996. Accounting classification and the predictive content of earnings. *Accounting Review* 71 (July): 337-355.

Fairfield, P. M. and T. Yohn. 2001. Using asset turnover and profit margin to forecast changes in profitability. *Review of Accounting Studies* 6 (December): 371-385.

Fairfield, P. M., S. Ramnath, and T. L. Yohn. 2009. Do industry-level analyses improve forecasts of financial performance? *Journal of Accounting Research* 47 (March): 147-178.

Fama, E. F. and J. D. MacBeth. 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy* 81 (May/June): 607-636.

Fama, E. F. and K. R. French. 1997. Industry costs of equity. *Journal of Financial Economics* 43 (February): 153-193.

Financial Accounting Standards Board (FASB). 1980. *Qualitative concepts of accounting information*. Statement of Financial Accounting Concepts No. 2. Norwalk, CT: FASB

-----. 1993. *Accounting for certain investments in debt and equity securities*. Statement of Financial Accounting Standards No. 115. Norwalk, CT: FASB

-----. 1998. *Accounting for derivative instruments and hedging activities*. Statement of Financial Accounting Standards No. 133. Norwalk, CT: FASB

-----. 2001. *Goodwill and other intangible assets*. Statement of Financial Accounting Standards No. 142. Norwalk, CT: FASB

-----. 2006. *Employers' accounting for defined benefit pension and other postretirement plans—an amendment of FASB statements No. 87, 88, 106, and 132(R)*. Statement of Financial Accounting Standards No. 158. Norwalk, CT: FASB

-----. 2008. *Discussion paper: Preliminary views on financial statement presentation*. Norwalk, CT

Financial Accounting Standards Board (FASB) and International Accounting Standards Board (IASB). 2008. Financial statement presentation--joint project of the IASB and FASB. http://www.fasb.org/project/financial_statement_presentation.shtml.

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

Francis, J. and M. Smith. 2005. A reexamination of the persistence of accruals and cash flows. *Journal of Accounting Research* 43 (June): 413-451.

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

Ghosh, A., Z. Gu, and P. C. Jain. 2005. Sustained earnings and revenue growth, earnings quality, and earnings response coefficients. *Review of Accounting Studies* 10 (March): 33-57.

Groysberg, B., P. Healy, and D. Maber. 2008. *What drives sell-side analyst compensation at high-status banks?* Working Paper: Harvard Business School.

Gu, Z. and T. Chen. 2004. Analysts' treatment of nonrecurring items in street earnings. *Journal of Accounting & Economics* 38 (December): 129-170.

Gu, Z. 2007. Across-sample incomparability of R^2s and additional evidence on value relevance changes over time. *Journal of Business Finance & Accounting* 34 (September/October): 1073-1098.

Hayn, C. 1995. The information content of losses. *Journal of Accounting & Economics* 20 (September): 125-153.

Hirshleifer, D. and S. H. Teoh. 2003. Limited attention, information disclosure, and financial reporting. *Journal of Accounting & Economics* 36: 337-386.

Jegadeesh, N. and J. Livnat. 2006. Revenue surprises and stock returns. *Journal of Accounting & Economics* 41 (April): 147-171.

Jennings, R. 1990. A note on interpreting "Incremental information content". *The Accounting Review* 65 (October): 925–932.

Jennings, R., P. J. Simko, and B. T. Robert, II. 1996. Does LIFO inventory accounting improve the income statement at the expense of the balance sheet? *Journal of Accounting Research* 34 (Spring): 85-109.

Landsman, W. R., B. L. Miller, and S. Yeh. 2007. Implications of components of income excluded from pro forma earnings for future profitability and equity valuation. *Journal of Business Finance & Accounting* 34 (April/May): 650-675.

Lev, B. and S. R. Thiagarajan. 1993. Fundamental information analysis. *Journal of Accounting Research* 31 (Autumn): 190-215.

Lipe, R. C. 1986. The information contained in the components of earnings. *Journal of Accounting Research* 24 (Supplement): 37-64.

Mest, D. P. and E. Plummer. 1999. Transitory and persistent earnings components as reflected in analysts' short-term and long-term earnings forecasts: Evidence from a nonlinear model. *International Journal of Forecasting* 15 (July): 291-308.

Mikhail, M. B., B. R. Walther, and R. H. Willis. 1999. Does forecast accuracy matter to security analysts? *Accounting Review* 74 (April): 185-200.

Ohlson, J. A. 1999. On transitory earnings. *Review of Accounting Studies* 4 (December): 145-162.

Ou, J. A. and S. H. Penman. 1989. Financial statement analysis and the prediction of stock returns. *Journal of Accounting & Economics* 11 (November): 295-329.

Plumlee, M. A. 2003. The effect of information complexity on analysts' use of that information. *The Accounting Review* 78 (January): 275-296.

Ramakrishnan, R. T. S. and J. K. Thomas. 1998. Valuation of permanent, transitory, and price-irrelevant components of reported earnings. *Journal of Accounting, Auditing & Finance* 13 (Summer): 301-336.

Ramanathan, R. 2002. *Introductory econometrics with applications* (5th ed.): Harcourt College Publishers.

Richardson, S. A., R. G. Sloan, M. T. Soliman, and I. Tuna. 2005. Accrual reliability, earnings persistence and stock prices. *Journal of Accounting and Economics* 39 (September): 437-485.

Rogers, W. 1993. Regression standard errors in clustered samples. *Stata Technical Bulletin* 13: 19-23.

Schmidt, A. P. 2006. The persistence, forecasting, and valuation implications of the tax change component of earnings. *The Accounting Review* 81 (May): 589-616.

Sloan, R. G. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review* 71 (July): 289-316.

Soliman, M. T. 2008. The use of DuPont analysis by market participants. *The Accounting Review* 83 (May): 823-853.

Stickel, S. E. 1991. Common stock returns surrounding earnings forecast revisions: More puzzling evidence. *The Accounting Review* 66 (April): 402-416.

Subramanyam, K. R. 1996. The pricing of discretionary accruals. *Journal of Accounting and Economics* 22 (August-December): 249-281.

Vuong, Q. H. 1989. Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica* 57 (March): 307-333.

Vita

Brian Michael Bratten is the son of Craig Bratten and Marcia Brenner and the step-son of Mark Brenner and Judy Bratten. He was born in Metairie, Louisiana in 1978. Brian attended high school in Cabot, Arkansas and Pearland, Texas. He earned a Bachelor of Business Administration in Accounting and a Master of Science in Finance at Texas A&M University, where he graduated in 2001. Prior to entering the doctoral program in Accounting at the University of Texas at Austin in 2004, Brian worked as a Senior Associate in audit at KPMG LLP in Houston, Texas. His research focuses on financial accounting and reporting. Brian is the husband of Kristy Michelle Bratten and the father of three sons, Benjamin, Elliott, and Joshua.

Permanent Address: brian.bratten@phd.mccombs.utexas.edu

This dissertation was typed by the author.