The Value of Earnings Comparability

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ABSTRACT

We develop a new metric of earnings comparability and study the capital market consequences of earnings comparability. The importance of comparability is expressed by regulators, teachers, practitioners, and researchers. The literature, however, lacks an empirical measure of financial statement comparability. More importantly, the "value" of comparability to users has not been established. We fill these gaps. We find that analyst following is increasing in earnings comparability, and that earnings comparability is positively associated with forecast accuracy and negatively related to bias in earnings forecasts. Our results suggest earnings comparability enhances a firm's information environment.

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The Value of Earnings Comparability

1. Introduction

Regulators, teachers, practitioners, and researchers all profess the importance of "comparability." According to the Securities and Exchange Commission (SEC) (2000), when investors judge the merits of investments and *comparability* of investments, efficient allocation of capital is facilitated and investor confidence nurtured. Financial statement analysis textbooks almost invariably stress the need to compare calculated ratios to various benchmarks, including ratios for the same firm in prior years, ratios for selected firms in the same industry, or ratios based on industry averages.[1] For instance, Stickney and Weil (2006) contend that, "Ratios, by themselves out of context, provide little information." In terms of research, there is also considerable demand for control firms that "match" firms of interest. Despite the frequent use of and the importance of comparability: 1) The literature lacks an empirical measure of financial statement comparability; and, 2) The "value" of financial statement comparability to users is not established in the literature.

We develop a measure of and study the capital market consequences of *earnings* comparability. A key innovation is the development of an empirical, firm-specific, output-based, quantitative measure of earnings comparability. We measure comparability based on financial statement outputs. In particular, we restrict our comparability measure to (arguably) the primary output of financial reporting: earnings. The measure is based on the strength of the historical covariance between a firm's earnings and the earnings of other firms in the same industry, as evidenced by higher R^2 values. While our primary focus is on creating a comparability measure

[1] See, e.g., Libby, Libby and Short (2004), Stickney and Weil (2006), Stickney, Brown, and Wahlen (2007), Revsine, Collins, and Johnson (2004), Wild, Subramanyam, and Halsey (2006), Penman (2006), White, Sondhi, and Fried (2002), and Palepu and Healy (2007).

at the firm level, we also produce a measure of relative comparability at the "firm-pair" level, in which a measure is calculated for all possible pairs of firms in the same industry.

Our measure is intended to capture comparability from the perspective of users, such as investors or analysts, who need to evaluate historical firm performance, predict future firm performance, or make other decisions using financial statement information. The measure contrasts with qualitative, attribute-based definitions of comparability. For instance, comparability can refer to comparable inputs such as similar business activities. Alternatively, comparability could refer to a system which translates similar inputs to comparable outputs (e.g., accounting comparability). Thus, one caveat of our measure is that, although it is possible that our output-based measure would be correlated with an input-based approach, it is not necessarily so.

The study comprises two sets of empirical analyses. The first part describes our firm-year measure of earnings comparability and provides descriptive properties of the measure. Because it is new, we provide construct validity of our measure of earnings comparability. We manually analyze the textual contents of a sub-sample of analysts' reports. We find that the likelihood of an analyst using another firm in the industry (say, firm *j*) as a benchmark when analyzing a particular firm (say, firm *i*) is increasing in the relative comparability between the two firms.

In the second part of the paper, we study the consequences of earnings comparability on the firm's information environment. Given a particular firm, we hypothesize that the availability of information about similar firms (as captured by our earnings comparability measure) lowers the cost of acquiring, and increases the overall quantity and quality of information available about the firm. Our results are consistent with this idea. We find that firms with higher comparability are more likely to be followed by more analysts. In a more precise prediction, our tests indicate that the likelihood of an analyst covering a particular firm (e.g., firm *i*) also covering another firm in the same industry (e.g., firm *j*) is increasing in the relative comparability between these two firms. These results suggest that the net benefits of higher earnings comparability for analysts outweighs the potential diminished benefit of reduced investor demand for a report on a firm that is highly comparable to another firm.

We also find that earnings comparability enables analysts to issue more accurate and less biased earnings forecasts. Thus, earnings comparability helps analysts more accurately forecast earnings and that the improvement comes, at least in part, through a reduction in forecast bias (i.e., optimism). This result is consistent with more comparable firms providing a richer information set. It is also consistent with acquiring information from sources other than management, which reduces the reliance on managements' private information, and hence decreases the incentive for analysts to strategically add optimistic bias to forecasts. Last, we do not find a significant relation between earnings comparability and forecast dispersion.

In some additional analysis, we construct a measure of stock return comparability that is analogous to our earnings comparability measure. It is based on the covariance of historical returns rather than earnings. We expect return comparability to better capture the economic comparability across firms. Return and earnings comparability are positively correlated, which provides additional validation and comfort that earnings comparability is in part explained by economic comparability. We also replicate our information environment tests including both earnings and return comparability in our regressions. Both the return and earnings comparability relations are generally significant in the expected (and identical) directions. Hence, earnings comparability is not subsumed by return comparability and must be capturing some differential effect. This result is consistent the existence of multiple dimensions of comparability, perhaps an economic dimension that captures both long-term cash flow expectations and growth options as well as a near-term, accounting-oriented dimension. It is also possible that both variables are measuring a single underlying comparability construct with error.

Our study contributes to the literature in a number of ways. First, we develop a measure of earnings comparability that likely captures user's notions of comparability and the benefits of comparability to them. We document tangible benefits for firms with higher comparability, such as improved analyst coverage, and benefits for users of financial statements issued by more comparable firms, such as improved forecasting. While comparability is generally and widely accepted as a valuable trait, there is little evidence beyond this study proving this.

Second, our measure can be used to help evaluate whether a firm (or regulatory) action that changes the economic transactions or the accounting of the transactions alters the comparability, from a users point of view. For example, according to the International Accounting Standards Committee Foundation (IASCF), the primary objective of the International Financial Reporting Standards (IFRS) is to develop a single set of "global accounting standards that require high quality, transparent and comparable information in financial statements and other financial reporting" (IASCF 2005). Our measure could be used to assess whether IFRS achieves the intended consequence of enhanced financial statement comparability (see e.g., Beuselinck, Joos, and Van der Meulen, 2007). More broadly, our measure can be used to assess the changes in earnings comparability as a result of changes in accounting earnings measurement rules or reporting standards, accounting choice differences, or of adjustments.

Third, researchers might use our measure of earnings comparability to help design more powerful tests. For instance, prior research highlights the importance of properly controlling for certain firm characteristics when testing hypotheses related to firm performance and earnings management (Barber and Lyon, 1996, 1997; Kothari, Leone, and Wasley, 2004). Our measure of earnings comparability could be used in this context to help identify a set of 'comparable' firms.

Last, our measure could assist practitioners, such as analyst and boards, in objectively choosing their choice of comparable firms. Currently, choosing comparables is often considered an "art form" (see Bhojraj and Lee, 2002) and the inherent discretion in this choice can lead to strategic behavior. For example, Lewellen, Park, and Ro (1996) show that firms' choices of industry and peer-company benchmarks are self serving. Thus, our measure could be used internally by firms or externally by investors to assess or validate this choice.

The paper proceeds as follows. Section 2 defines our earnings comparability measure and provides construct validity tests of the measure. Section 3 outlines our predictions that earnings comparability improves a firm's information environment. Section 4 presents the results of our tests. Section 5 provides some additional analysis that incorporates the return comparability measure. The last section concludes.

2. A measure of earnings comparability

In this section, we first describe the demand for comparable information and then explain how we compute our measure of earnings comparability. In addition, since our measure of earnings comparability is novel, we provide descriptive information on the measure's properties to ascertain the measure's construct validity.

2.1. Demand for comparable information

Comparability is widely accepted as a desirable attribute. From a regulatory perspective, in addition to the views of the SEC, the usefulness of *comparable* financial statements is underscored in the Financial Accounting Standards Board (FASB) accounting concepts statement. Specifically, the FASB (1980, p. 40) states that "investing and lending decisions essentially involve evaluations of alternative opportunities, and they cannot be made rationally if *comparative* information is not available" (Our emphasis). Comparability is also one of three qualitative characteristics of accounting information included in the accounting conceptual framework (along with relevance and reliability). Further, according to the FASB (1980, p. 40), "The difficulty in making financial comparisons among enterprises because of the different accounting methods has been accepted for many years as the principal reason for the development of accounting standards." Here, the FASB argues that users' demand for comparable information drives accounting regulation.

In terms of teaching and practice, there is significant demand for benchmarks to evaluate, predict, or justify a number or ratio. Penman (2006) states: "To make judgments about a firm's performance the analyst needs benchmarks. Benchmarks are established by reference to other firms (usually in the same industry) or to the same firm's past history." Koller et al. (2005) contend that a carefully designed price multiples analysis can provide valuable insights about the company and its competitors, and recommend that analysts choose firms with similar prospects. In addition, the actual use of price multiples in valuation by sell-side analysts is ubiquitous (Bhojraj and Lee, 2002; Asquith et al., 2005). This drives demand for comparable firms that help analysts to evaluate and predict future price multiples. Last, firms must report to regulators a comparison of their stock performance with a set of comparable firms or an index as benchmarks for compensation purposes (see, e.g., Lewellen, Park, and Ro, 1996).

In terms of research, there is demand to control for firms' underlying economics. This is often done by including industry fixed effects, so that the analysis focuses on within-industry variation or by using a matched-pair design. These control firms are often chosen such that industry, size, book-market ratios, and the previous year's financial performance are similar to the treatment firm (see, e.g., Barber and Lyon 1996, 1997; Kothari, Leone and Wasley, 2005). There could also be demand in terms of contracting research. For example, Albuquerque (2006) finds that improvements in determining who peer firms are improves the ability to identify relative performance evaluation.

2.2. Measuring earnings comparability

The term comparability in accounting textbooks, in regulatory pronouncements, and in academic research is defined broadly and imprecisely. For instance, comparability could refer to comparable *inputs* such as similar accounting methods, business activities, or industry membership. As an example, Bradshaw and Miller (2007) study whether firms that intent to harmonize their accounting with US GAAP change to US GAAP accounting methods. DeFond and Hung (2003) argue that accounting choice heterogeneity (e.g., differences in inventory methods such as LIFO versus FIFO) increases the difficulty in comparing earnings across firms. Alternatively, comparability might be defined as a function of outputs such as similar earnings and financial ratios. We adopt the perspective of a user of financial statements, such as an investor or analyst, and focus on financial statement *outputs*. In particular, we develop our measure of comparability using one primary output of financial reporting, namely, earnings. Our user perspective is important and consistent with the benefits we analyze (discussed below), which are from the perspective of users (in particular, financial analysts).

We begin by proposing a measure of comparability that is intuitively consistent with the definition of comparability implicit in accounting standards and the professional literature on financial statement analysis. As mentioned above, we teach and emphasize in any lesson on financial statement analysis that it is difficult to draw meaningful inferences about a financial measure unless there is a "comparable" benchmark. FASB (1980, p. 40) echoes this point. Implicit is the idea that better benchmarks produce better inferences (e.g., better evaluation of firm performance, better prediction of next year's price-multiple, etc.). We expect that similar firms will provide better benchmarks for each other. Hence the quality of information is higher. As an additional consideration, the expectation of information transfer among similar firms is also much higher. Thus the cost of acquiring information is lower.

To identify similar firms, we calculate the historical covariance of quarterly earnings between all possible pairs of firms in the same industry. We sort firms based on the ability of other firms' earnings to predict the respective firm's earnings. Ceteris paribus, firms with higher comparability are firms in which earnings covary more with the earnings of other firms in the industry, as evidenced by higher R^2 values. If firms are similar, they are more likely to experience similar economic shocks. For instance, a change in input prices or shifts in consumer demand for firms with similar business models should translate into similar changes in economic profitability. These firms are also likely to account for economic transactions in a similar way. In contrast, if business models are different, or firms are sensitive to different types of shocks, or the accounting is different, then we would not expect to see earnings covary over time.

More specifically, earnings comparability is defined as follows. We first estimate:

$$Earnings_{ijt} = \Phi_{0ij} + \Phi_{1ij}\, Earnings_{jt} + \varepsilon_{ijt}. \quad (1)$$

We measure *Earnings* as the ratio of quarterly net income before extraordinary items (data8) to the average total assets (data44), taken from the Compustat Quarterly file. To determine the most comparable firm *j* for each firm *i*, we estimate Equation (1) for each firm *i* – firm *j* pair, ($i \neq j$), *j* = 1 to *J* firms in the same 2-digit SIC industry with available data. We require 16 quarters of data available for each firm *i* – firm *j* combination and we estimate Equation (1) at the end of December for each year. We also restrict the sample to firms whose fiscal year ends in March, June, September, or December. This ensures that *i* and *j* firms' earnings are measured at the end of the same fiscal quarter. In order to avoid the influence of outliers, we remove observations in which *Earnings* for firm *i* is more than three standard deviations from the mean value of the 16 *Earnings* observations for firm *i* used to estimate Equation (1).

After estimating the R^2 for regression model (1) for each firm *i* – firm *j* combination, we rank all *J* values of R^2s for each firm *i* from the highest to lowest R^2. The most comparable firm is the one that produces the highest R^2. *Comp4* is the average R^2 for the four firms with the highest R^2. *CompInd* is the average R^2 for all firms in the industry.[2] These are the two comparability measures we use in our tests. The idea is that firms with high *Comp4* and *CompInd* are firms for which earnings variation is better explained by variation in the earnings of other firms in the same industry.

Before proceeding further, we discuss measures used in other studies that are indirectly related to ours. First, existing measures of comparability in the literature are based mainly on similarities in cross-sectional *levels* of contemporaneous measures (e.g., return on equity, firm

[2] Admittedly, the choice of how many firms should be included in the set of comparable firms is *ad hoc*. In untabulated analyses, we use the R^2 from the single most comparable firm as well as the average R^2 from the top ten firms. The results for the single most comparable firm seem to be slightly weaker, while the results for the top ten firms are similar to using the top-four firms.

size, price multiples) at a point in time. Joos and Lang (1994) study the comparability of accounting data in a European setting. They expect that improved accounting comparability between countries will result in smaller differences between accounting measures of profitability (i.e., ROE), between valuation multiples of accounting data (i.e., Earnings/Price; Book value/Market value of equity), and between the degree of association between accounting and stock data (i.e., value relevance). Land and Lang (2002) also focus on comparing valuation multiples across countries. These measures are typically estimated in *aggregate* at the country level. Another set of literature attempts, for each treatment firm, to find the closest matching firm. This is often done by restricting the set of matched firms along certain dimensions, such as similar industry, size quintiles, etc. and perhaps minimizing the distance along a particular dimension such as return on equity (see, e.g., Barber and Lyon 1996, 1997; Kothari, Leone and Wasley, 2005). Our measure is more dynamic, capturing similarities in *co-variation* over time, and is *firm-specific*.[3]

Second, our measure of earnings comparability is related to the previously-established time-series concept of earnings "predictability" in which earnings are regressed on previous-period earnings (e.g., Lipe 1990). We estimate firms' predictability from the following time-series model (this measure is used below in our tests):

$$Earnings_{it} = \Phi_{0i} + \Phi_{1i}\, Earnings_{it-4} + \varepsilon_{it}. \qquad (2)$$

The model is estimated for each firm *i* over a rolling 16-quarter window.[4] *Predictability* is defined as the R^2 from Equation (2). This is a firm-specific measure of predictability.

[3] Interesting exceptions are studies that examine the returns to pairs trading, such as Papadakis and Wysocki (2007). They identify pairs of similar firms using the average difference in daily "normalized" price over a 12-month period. In effect, their measure captures a blend of similar levels *and* similar covariation over time.

[4] We focus on quarterly predictability, which aligns with our earnings comparability measure derived from quarterly earnings. Much of the prior research focuses on annual predictability, typically estimated per firm over a rolling 10-year window using annual earnings (Lipe 1990; Francis, LaFond, Olsson, and Schipper, 2004).

Predictability, all else equal, is desirable since one important task investors perform is forecasting future earnings for the purpose of valuing their securities. In essence, our earnings comparability measure is a cross-sectional version of predictability. While earnings predictability or persistence measures have been around in the literature for quite some time (see, e.g., Lipe 1990, and Francis, LaFond, Olsson, and Schipper, 2004), their use in developing a comparability measure in this study is unique.

Third, Piotroski and Roulstone (2004), and Chan and Hameed (2006), among others, study stock price synchronicity, which is based on the R^2 from a regression of firm's stock returns on market and industry stock returns. They are inherently interested in the type of information (firm, industry, or market) impounded in stock prices. We highlight that our measure is based solely on accounting data, and is hence not sensitive to flows of non-accounting information, to investor's interpretation, or to assumptions about market efficiency. Our measure could also be applied to private firms.

Fourth, an older literature studies the accounting beta, which captures the relation between earnings at the firm level and earnings at the industry or market level. Brown and Ball (1967) show that firm earnings can be explained in part by the earnings of other firms in the same industry and the earnings of all firms in the market. This research focuses on documenting that the market beta (from a capital asset pricing model) is positively related to the accounting beta (see, e.g., Beaver, Kettler, and Scholes 1970; Beaver and Manegold 1975; Gonedes 1973, 1975).

2.3. Sample and descriptive statistics

To estimate earnings comparability, we obtain quarterly accounting data from *Compustat* starting in 1991. As discussed above, we require 16 quarters of net income before extraordinary items data for a given firm *i* (in addition to 16 quarters for firm *j*). We exclude holding firms. In some cases, Compustat contains financial statements for both the parent and the subsidiary company, and we want to avoid matching such two firms. We exclude ADRs and limited partnerships because our focus is on corporations domiciled in the United States.[5] We also exclude firms that have names highly similar to each other using an algorithm that matches five-or-more-letter words in the firm names, but avoids matching on generic words such as "hotels", "foods", "semiconductor", etc. Finally, we restrict the sample to industries with at least 20 firms per year based on the SIC two-digit classification. These restrictions result in a sample of 42,336 firm years (about 3,500 firms per year) with available data to estimate earnings comparability during 1994 to 2005. In addition, in our later analysis we restrict the sample to firms followed by analysts. We use data from IBES for all our analyst measures. This restriction reduces the sample to 20,508 firm-year observations with the comparability score and analyst coverage. We term the former the unrestricted sample and the latter the analyst-restricted sample. The analyst-restricted sample is biased towards larger and more-frequently-trading firms.

Table 1 presents descriptive statistics for our measure of earnings comparability. Panel A presents the number of observations and the means for *Comp4* and *CompInd* by year for the unrestricted and analyst-restricted samples. The mean value for *Comp4* ranges from 50.3% to 54.5% for the unrestricted sample. For the average firm in our sample, the four firms in the same industry with the highest earnings correlation explain about half the variability of the sample firm's earnings. Likewise, the *CompInd* mean, i.e., the average R^2 for Equation (1) for all firms in the industry is about 11-12%. The results are similar for the analyst-restricted sample except that the comparability scores are slightly higher.

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[5] Specifically if the word Holding, Group, ADR, or LP (and associated variations of these words) appear in the firm name on Compustat, the firm is excluded.

[Table 1]

Panel B presents descriptive statistics for the unrestricted sample. We note that *Comp4* and *CompInd* present considerable cross-sectional variation. For instance, the 10^{th} percentile and the 90^{th} percentile for *Comp4* equal 32.5% and 73.6%, respectively. In addition, for comparison, Panel B also presents descriptive statistics for *Predictability*, which is defined as the R^2 of a regression of earnings on prior-year earnings as described in Equation (2). In this case, the mean predictability score is 15.9% which means that for the average firm in the sample, prior earnings explain about 16% of the variability in one-year ahead earnings. Finally, Panel C presents Pearson correlations among the three variables. As expected, the two comparability measures are highly correlated (correlation coefficient of 0.71). In addition, comparability is also positively correlated with firm predictability.

2.4. Validating our earnings comparability measure

In this section, we describe a test aimed at providing construct validity of our earnings comparability measure. An assumption implicit in this test is that, for any given firm, investors and analysts know the identity of comparable firms (if any). Investors and analysts have access to a broad information set about each firm, which goes beyond the historical financial statements, and includes firms' business models, competitive positioning, markets, products, etc. While the actions and analyses of investors might be largely private, analysts' output (e.g., earnings forecasts) and analyses (e.g., their reports) are observable. Hence, our tests focus on analysts.

We provide a testable prediction to establish our measure's construct validity. This prediction relates to the important assumption underlying our measure, namely, that the ranking of R^2s from pairwise firm *i* - firm *j* regressions in fact identifies a set of comparable firms for firm *i*. We predict that if an analyst issues a report about firm *i*, then we expect her to more likely use firms that are "comparable" to firm *i* in her reports. The typical analyst report context is that the analyst desires to evaluate the current, or justify her predicted, firm valuation multiple, (e.g., Price/Earnings ratio), using a relative analysis of similar firms' valuation multiples as benchmarks. Evidence from a test of this prediction suggests our assumption is valid.

The comparable firms that an analyst uses in her analysis are not available in a machine-readable form in existing databases. We hand collect a sample of analyst reports from Investext and manually extract this information from the reports. The cost of hand collecting this information limits the size of this sample. Reports are chosen as follows. We randomly select 350 firms (i.e., firm *i*'s) in our sample with available data for the year 2005. For these firms, we search Investext to find up to three reports per firm *i*, each report written by a different analyst, that refer to "comparable" or "peer" firms (i.e., potential firm *j*'s) in the report. We then record the name and ticker of all firms used by the analyst as a peer or comparable firm for firm *i*. We match these peer firms with Compustat using the firm name and ticker. In total, we obtain 150 reports written by 126 unique analysts for 98 unique firms. Each report mentions one or more firms as comparable to the firm for which the analyst has issued the report.[6]

For our tests, we estimate the following logistic regression:

$$UseAsComp_{ikj} = \alpha + \beta_1\, ijRSQ_{ij} + \gamma\, Controls_j + \varepsilon_{ikj}. \tag{3}$$

UseAsComp is an indicator variable that equals one if analyst *k* who *writes a report* about firm *i* refers to firm *j* as a comparable firm in her report, and equals zero otherwise. *ijRSQ* is the R^2 from the estimation of Equation (1) for each firm *i* – firm *j* pair in our sample. We predict that the probability of an analyst using firm *j* in her report is increasing in *ijRSQ*. We use *Size*,

[6] Part of the reason this process is labor intensive is because we do not know ex ante whether Investext covers firm *i*, and because not all analysts discuss comparable firms in their analysis. For example, many reports represent simple updates with no discussion of valuation methods. In other cases, analysts rely more heavily on a discounted flow analysis or use historical valuation multiples to predict future multiples. We exclude reports on Investext that are computer generated or not written by sell-side analysts.

Volume, *Book-Market*, *ROA*, and industry fixed effects as control variables. Our choice of these controls follows their common use by other researchers who match control firms with treatment firms along these three dimensions (see, e.g., Barber and Lyon, 1996, 1997; Kothari, Leone, and Wasley, 2005). In addition to the levels of these variables, we control for the *differences* in characteristics between firm *i* and firm *j*. The intuition for using both levels and differences is as follows: An analyst who reports on firm *i* is more likely to use a firm as a peer if the firm has similar (comparable) characteristics (e.g., similar size, growth potential and profitability) to firm *i*. This implies the larger the difference between firm *i* and firm *j,* the less likely it is to be covered by the analyst. However, large, high-growth, and highly-profitable firms are more likely to be covered by an analyst and recognized by investors, which motivates us to also include the levels of these firm characteristics in the regression.

Table 2 presents the logistic regressions for model (3). The coefficient on *ijRSQ* is positive and statistically significant in both columns as predicted. This suggests that as the *ijRSQ* increases, it increases the odds of an analyst using firm *j* as a peer firm in a report about firm *i*. While the coefficients on *Book-Market* and *ROA* are not significant, the coefficients on *Size* and *Volume* are positive and statistically significant. In addition, the estimated coefficients of the *differences* in the control variables between firm *i* and firm *j* are all negative and significant suggesting that analysts tend to more likely use firms as peers if they are similar along these dimensions.

[Table 2]

Overall, the results in Table 2 support the notion that an analyst who writes a report about a firm will more likely choose benchmark firms that have higher values of our earnings comparability measure. This bolsters the construct validity of our earnings comparability measure.

3. Hypotheses: Capital market consequences of earnings comparability

In this section, we develop hypotheses about the capital market consequences of earnings comparability. As mentioned above, while we are interested in both investors and analysts, given the rich publicly-available information on analysts, we focus on their outputs (i.e., earnings forecasts). We predict that higher earnings comparability lowers analysts' cost of understanding the firm and evaluating its performance. In addition, we expect the net information set for comparable firms to be of higher quantity and quality. This richer information set facilitates analysts' ability to forecast firm *i*'s earnings when these other firms are comparable. Hence, we expect that in the cross-section, higher comparability will be associated with better information environments. We investigate two dimensions of analysts' behavior – the number of analysts following a firm and the properties of analyst forecasts.

Our first hypothesis examines whether comparability affects analyst coverage. As discussed in Bhushan (1989) and in Lang and Lundholm (1996), the number of analysts following a firm is a function of the analysts' costs and benefits. We argue that, ceteris paribus, because firms with higher comparability have richer information sets, it is easier to analyze these firms, and so more analysts should cover these firms. Our first hypothesis (in alternate form) is:

> H1: *Ceteris paribus, earnings comparability is positively associated with analyst coverage.*

An argument consistent with the null hypothesis is that the better information environment associated with higher-comparability firms will decrease the investor demand for analyst coverage. That is, the benefits to analysts will decrease as well. However, the literature on analysts suggests that analysts primarily interpret information as opposed to convey new information to the capital markets (Lang and Lundholm 1996; Francis, Schipper, and Vincent 2002; Frankel, Kothari, and Weber, 2006; De Franco, 2007). As a specific example, Lang and Lundholm (1996) find that analyst coverage is increasing in firm disclosure quality. These empirical findings suggest that an increase in the supply of information results in higher analyst coverage, consistent with the lower costs of more information outweighing the potentially lower benefit of decreased demand. These findings in the literature support our signed prediction.

Our second set of hypotheses examines the association between earnings comparability and the properties of analyst earnings forecasts. The first property we examine is forecast accuracy. To the extent that comparability facilitates investors' ability to forecast firm *i*'s earnings the accuracy of earnings forecasts should, ceteris paribus, increase with earnings comparability. For example, the existence of comparable firms could allow analysts to better explain firms' historical performance or to use information from comparable firms as an additional input in their earnings forecasts. Our hypothesis 2a (in alternative form) is:

> H2a: *Ceteris paribus, earnings comparability is positively associated with analyst forecast accuracy.*

Second, prior research finds analysts' long-horizon forecasts are optimistic on average (e.g., O'Brien, 1988, and Richardson et al., 2004).[7] Francis and Philbrick (1993), Das et al. (1998), and Lim (2001) show that part of the bias in analyst forecasts is explained by analysts adding optimism to their forecasts to gain access to management's private information, which helps improve forecast accuracy.[8] If information from comparable firms serves as a substitute for managements' private information, then the incentive to strategically add optimistic bias to

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[7] Analyst optimism has decreased over time and is more-pronounced for longer-horizon forecasts and it seems to be driven by relatively few observations (Brown 2001; Lim 2001; Gu and Wu 2003; Richardson et al. 2004).

[8] Recent research by Eames et al. (2002) and Eames and Glover (2003) question these results.

gain access to management is reduced. Further, if more objective information from comparable firms is available, it is easier to identify when (i.e., catch) analysts act strategically, which hence increases the cost to the analyst of this behavior. Therefore analysts' forecasts of higher-comparability firms should be less optimistic. We state this prediction as hypothesis 2b (in alternate form):

> H2b: *Ceteris paribus, earnings comparability is negatively related to analyst forecast optimism.*

Third, we investigate the relation between earnings comparability and analyst forecast dispersion. If analysts have the same forecasting model, and if higher comparability implies the availability of superior public information, then an analyst's optimal forecast will place more weight on public information and less on her private information. This implies comparability will reduce forecast dispersion. Our hypothesis 2c (in alternative form) is:

> H2c: *Ceteris paribus, earnings comparability is negatively associated with forecast dispersion.*

We acknowledge that superior public information via higher comparability could generate more dispersed forecasts, which would support the null of hypothesis 2c. The intuition here is that if analysts process a given piece of information differently from other analysts, then the availability of greater amounts of public information for comparable firms will generate more highly-dispersed forecasts. At least two theoretical studies predict such a phenomenon. Harris and Raviv (1993) and Kandel and Pearson (1995) develop models in which disclosure promotes divergence in beliefs. Kim and Verrecchia (1994) allow investors to interpret firm disclosures differently, whereby better disclosure is associated with more private information production.

4. Empirical Tests

4.1. Analyst coverage tests

To test whether analyst coverage and comparability are positively related, our first hypothesis, we estimate the following regression:

$$Coverage_{it+1} = \alpha + \beta_1\, Comparability_{it} + \beta_2\, Predictability_{it} + \gamma\, Controls_{it} + \varepsilon_{it+1}. \qquad (4)$$

Coverage is the logarithm of the number of analysts issuing an annual forecast for firm *i* in year *t*. *Comparability* is either *Comp4* or *CompInd*. We include *Predictability* in our specification because it represents a natural benchmark to assess the economic significance of our comparability measure. Predictability is based on a statistical model, like comparability. More importantly, predictability is accepted in the literature as a desirable earnings attribute (Schipper and Vincent, 2003; Francis et al., 2004).

In estimating model (4), we control for other factors motivating an analyst to cover firm *j* by including the determinants of analyst coverage previously documented in the literature (e.g., Bhushan, 1989, O'Brien and Bhushan, 1990, Brennan and Hughes, 1991, Lang and Lundholm, 1996, and Barth, Kasznik, and McNichols, 2001). *Size* is the logarithm of the market value of equity measured at the end of the year. *Volume* is the logarithm of trading volume in millions of shares during the year. *Issue* is an indicator variable that equals one if the firm issues debt or equity securities during the years *t-1*, *t*, or *t+1*, and zero otherwise. *Book-Market* is the ratio of the book value to the market value of equity. *R&D* is research and development expense scaled by total sales. *Depreciation* is depreciation expense scaled by total sales. Throughout the remaining analysis, for continuous variables that we do not take the logarithm of, we delete observations if these variable values fall in the lowest or highest percentile of their respective distributions, calculated annually (i.e., we trim the data annually at the 1% and 99% percentile).

We also include industry and year fixed effects. Because the estimation of Equation (4) is likely to suffer from time-series dependence, we estimate the model as a panel and cluster the standard errors at the firm level (in addition to the year fixed-effects).

As seen in Table 1, we have 20,508 firm years with comparability scores in the analyst-restricted sample. In order to test hypothesis 1, we further restrict the sample to firms with available data to compute the control variables. This reduces the sample to 18,735 firm-year observations from 1994 to 2005.

Table 3, Panel A presents descriptive statistics for the variables included in this analysis. An average (median) firm in our sample is covered by 7 (4) analysts (see the variable *Coverage-N*, which is the number of analysts issuing a forecast for the firm). The mean value for *Comp4* (*CompInd*) is 0.55 (0.12), which is similar to the means of these variables presented in Table 1. Turning to the control variables, the average firm in the sample has a market value of $2.7 billion (see the variable *Size-$M*, which is the firm's market value of equity measured in $millions) and a *Book-Market* of 0.54. Panel B presents the correlation matrix. Consistent with prior research we find that *Coverage* is positively correlated with firm size and trading volume, and is negatively correlated with the book-market ratio. More importantly, *Coverage* is positively correlated with both measures of earnings comparability.

[Table 3]

Table 4 presents the regression results. Both of the earnings comparability measures are positively associated with analyst coverage and the results are robust to the inclusion of earnings predictability in the model. In terms of economic significance, an increase from the 10^{th} to the 90^{th} percentile in *Comp4* (*CompInd*) is associated with an increase of 0.40 (0.35) analysts. Given that the median coverage in our sample is four analysts this represents an increase of almost

10%, suggesting that the effect is also economically significant. Consistent with prior research, we find that analyst following is increasing in firm size and trading volume. However, we find an inconsistent coefficient for *Book-Market*. Overall, the regression results in Table 4 confirm the univariate findings in Panel B of Table 3, and are consistent with hypothesis 1 that predicts a positive association between analyst coverage and earnings comparability. It suggests the net benefits of covering firms with high comparability (due to the richer information environment) outweigh the potential decreased benefit from investors' reduced demand for information about highly-comparable firms.

[Table 4]

4.2. Analyst coverage of other firms conditional on covering a particular firm

We now provide additional evidence of higher analyst coverage, our first hypothesis, in the form of a more precise prediction about which firms an analyst will cover. We expect that the likelihood of an analyst covering a particular firm (e.g., firm *i*) also covering another firm in the same industry (e.g., firm *j*) is increasing in the relative comparability between these two firms. Hence, we not only predict that higher earnings comparability leads to more analysts covering the firm, but also specifically predict which other firms the analyst will follow.

We estimate the following logistic regression for each year of our sample:

$$CondCoverage_{ikj} = \alpha + \beta_1\, ijRSQ_{ij} + \gamma\, Controls_j + \varepsilon_{ikj}. \tag{5}$$

CondCoverage is an indicator variable that equals one if analyst *k* who *covers* firm *i* also covers firm *j*, and equals zero otherwise. An analyst "covers" a firm if she issues at least one annual forecast about the firm. We predict that the probability of covering firm *j* is increasing in *ijRSQ*. We use the same variables as in Equation (4) to control for other factors that could explain analyst coverage (but measured for firm *j*).

The annual sample for this test is quite large. For firm *i*, there are *K* analysts who cover the firm. For each firm *i* – analyst *k* pair there are *J* firms in the same industry as firm *i*. Hence, our sample consists of *I* firms × *K* analysts × *J* firms. In addition to requiring valid data for all our measures, we require each analyst *k* to cover at least five firms. In estimating the model, we rely on the coverage choice of an analyst within an industry, and therefore require the availability of at least a few observations per analyst per industry for which *CondCoverage* equals one. This restriction should exclude junior analysts, analysts in transition, and data-coding errors. We exclude analysts who cover more than 40 firms. Covering greater than 40 firms is rare (less than one percent of analysts) and could be a data-coding error in that the observations could refer to the firm employing the analyst rather than an individual analyst at the firm.

In Table 5, we provide the mean, maximum, and minimum coefficient from the 12 annual logistic regressions. The large sample size (average annual sample used in our tests consists of 2,904,641 firm *i* – analyst *k* – firm *j* observations) prohibits us from estimating a panel regression. The mean coefficient *t*-statistic is based on the distribution of the 12 annual coefficients using the Fama and MacBeth (1973) procedure. Further, we adjust for potential time-series dependence in the estimates using the Newey-West (1987) correction with one lag (In untabulated tests we find that higher lags lead to higher t-stats. Thus we present the conservative estimate.). The mean coefficient on *ijRSQ* is positive and statistically significant as predicted. In addition, the coefficient is positive in all 12 years. The result suggests that the firm *j*'s we identify as "comparable" to firm *i* are more likely to be followed by the analysts who also cover firm *i*. The coefficients on the control variables generally correspond with the direction documented in the literature. For example, analyst coverage is increasing in firm size, trading volume, research and development, and depreciation.

[Table 5]

Overall, the results in Table 5 present evidence that the likelihood of an analyst covering firm *j,* conditional on the analyst covering firm *i,* is increasing in the extent of the comovement of the earnings of firms *i* and *j,* i.e., the pair-wise earnings R^2. This provides additional evidence consistent with higher comparability of earnings reducing the cost of covering the firm.[9]

4.3. Forecast accuracy, optimism, and dispersion tests

To test our hypotheses about whether comparability affects forecast accuracy, optimistic bias, and dispersion, we estimate the following specification:

$$Forecast\ Metric_{it+1} = \alpha + \beta_1\ Comparability_{it} + \beta_2\ Predictability_{it} + \gamma\ Controls_{it} + \varepsilon_{it+1}. \quad (6)$$

Forecast Metric is *Accuracy*, *Optimism*, or *Dispersion*. Analyst forecast accuracy is the absolute value of the forecast error multiplied by -1:

$$Accuracy_{it} = |Fcst\ EPS_{it} - Actual\ EPS_{it}|/Price_{it-1} \times -1. \quad (7)$$

$Fcst\ EPS_{it}$ is analysts' mean I/B/E/S forecast of firm-*i*'s annual earnings for year *t*. For a given fiscal year (e.g., December of year *t+1*) we collect the earliest forecast available during the year (i.e., we use the earliest forecast from January to December of year *t+1* for a December fiscal year-end firm). $Actual\ EPS_{it}$ is the actual amount announced by firm *i* for fiscal period *t+1* as reported by I/B/E/S. *Price* is the stock price at the end of the prior fiscal year. Because the absolute forecast error is multiplied by -1, higher values of *Accuracy* imply more accurate forecasts.

We measure optimism in analysts' forecasts using the signed forecast error:

$$Optimism_{it} = (Fcst\ EPS_{it} - Actual\ EPS_{it})/Price_{it-1}. \quad (8)$$

[9] This result is related to a study by Ramnath (2002) who shows that there is information transfer between firms covered by the same analyst. He shows that among these firms, the earnings announcement surprises of firms that announce first are systematically related to forecast revisions for the other firms that the analysts cover.

Dispersion is the cross-sectional standard deviation of individual analysts' annual forecasts for a given firm, scaled by price. Hypothesis 2 predicts that accuracy is increasing in earnings comparability, and that optimism and dispersion are decreasing in earnings comparability.

We control for other determinants of these forecast metrics as previously documented in the literature. *SUE* is the absolute value of firm *i*'s unexpected earnings in year *t* scaled by the stock price at the end of the prior year. Unexpected earnings are actual earnings minus the earnings from prior year. Firms with greater variability are more difficult to forecast, so forecast errors should be greater (e.g., Kross, Ro and Schroeder, 1990, and Lang and Lundholm, 1996). Consistent with Heflin, Subramanyam and Zhang (2003), earnings with more transitory components should also be more difficult to forecast. We include the following three variables to proxy for the difficulty in forecasting earnings. *Neg UE* equals one if firm *i*'s earnings are below the reported earnings a year ago, zero otherwise. *Loss* equals one if the current earnings is less than zero, zero otherwise. *Neg SI* equals the absolute value of the special item deflated by total assets if negative, zero otherwise. We expect these three variables to be positively related to optimism given that optimism is greater when realized earnings are more negative.

$Days_{it}$ is a measure of the forecast horizon, calculated as the logarithm of the number of days from the forecast date to firm-*i*'s earnings announcement date. The literature shows that forecast horizon strongly affects accuracy and optimism (Sinha et al., 1997, Clement, 1999, and Brown and Mohd, 2003). Last, we include industry and year fixed effects. Similar to the estimation of Equation (4), we estimate the model as a panel and cluster the standard errors at the firm level.

After computing forecast accuracy and the control variables for these tests, the final sample is reduced to 17,178 firm-year observations. The final sample is smaller still for the tests of dispersion because the standard deviation requires at least 3 analysts for a given firm. Table 6 presents descriptive statistics (Panel A) and the correlation matrix (Panel B) for the variables included in the analysis. Mean accuracy is 4.2% of share price. Mean optimism is 2.5% of share price, which is consistent with prior research that analysts tend to be optimistic on average. However, the median is only 0.2%, also consistent with previous research. The mean forecast dispersion is 0.7% of share price. In terms of correlations, we find that the earnings comparability measures are positively correlated with forecast accuracy, and negatively correlated with forecast bias.

[Table 6]

Table 7 presents the regression results for all three forecast metrics. The first two columns present results for forecast accuracy. With respect to the earnings comparability measures, our primary variables of interest, we find that comparability is positively associated with accuracy. In terms of economic significance, an increase from the 10^{th} to the 90^{th} percentile in *Comp4* (*CompInd*) is associated with an increase in accuracy of about 0.67% (0.45%). This represents an improvement in accuracy of about 10-15% for the average firm in the sample. This result supports hypothesis 2a that higher earnings comparability increases the accuracy of analysts' forecasts. With respect to the control variables, we find that forecast accuracy is positively associated with earnings predictability. Further, accuracy is decreasing in the incidence of losses and in the variability of earnings. In addition, forecast accuracy is also decreasing in the forecast horizon (i.e., the time between forecast and announcement date).

[Table 7]

The next two columns in Table 7 present the results for forecast optimism. In this case, we find that analyst optimism is greater for firms reporting losses or firms reporting a decrease in earnings, consistent with our predictions. As with forecast accuracy, the result is also economically significant suggesting a reduction in analyst optimism of about 20% for the average firm in the sample. Also, analyst optimism is increasing in forecast horizon consistent with prior findings that optimism decreases as it gets closer to the end of the fiscal year (Richardson, Teoh, and Wysocki, 2004). We also find a small, albeit insignificant, relation between optimism and earnings predictability. In support of our hypothesis 2b, we find a consistent negative relation between our measures of earnings comparability and analyst optimism. Together with the findings using forecast accuracy, these results suggest that one way earnings comparability improves forecast accuracy is via the reduction of analyst optimism.

The results for forecast dispersion are presented in the last two columns of Table 7. Forecast dispersion is decreasing in earnings predictability, and increasing in earnings surprises, the incidence of losses, and the forecast horizon. However, we fail to find a significant negative relation between earnings comparability and forecast dispersion.

5. Earnings and return comparability

The results above suggest that earnings comparability is associated with higher analyst coverage, higher analyst forecast accuracy, and lower analyst forecast bias. However, one unanswered question is whether the value of comparability could be observed solely through stock prices. This could occur if earnings comparability mainly captures economic comparability, which in turn could be better approximated by return comparability. Certainly, analysts are focused strongly on valuing the firm and issuing buy and sell recommendations to investors, based on expected future price changes. The alternative is that earnings comparability enriches the information environment (beyond the information in stock prices) such that it leads to more analyst coverage and enhanced analyst-forecasting ability. In support of the alternative, analysts spend a significant amount of effort producing initial and regularly updating earnings forecasts. This task is consistent with an earnings dimension being important to analysts.

To answer these questions we create a measure of return comparability that parallels the construction of our earnings comparability measure. Specifically, we estimate:

$$StockReturn_{ijt} = \Phi_{0ij} + \Phi_{1ij}\, StockReturn_{jt} + \varepsilon_{ijt}. \tag{9}$$

StockReturn is the monthly stock return of the firm in a given month, taken from the CRSP Monthly Stock file. To determine the most comparable firm j for each firm i, we estimate Equation (9) for each firm i – firm j pair, ($i \neq j$), j = 1 to J firms in the same 2-digit SIC industry with available data. We require 48 months of data available for each firm i – firm j combination. This four-year period is consistent with the 16-quarter requirement for earnings comparability. We estimate Equation (9) at the end of December for each year. We also restrict the sample to firms whose fiscal year ends in March, June, September, or December. Similarly to the procedure used to estimate earnings comparability, after estimating the R^2 for regression model (9) for each firm i – firm j combination, we rank all J values of R^2s for each firm i from the highest to lowest R^2. *Comp4 Ret* is the average R^2 for the four firms with the highest R^2. *CompInd Ret* is the average R^2 for all firms in the industry.

Tables 8 and 9 reports the results of the Tables 4 (analyst coverage) and 7 (analysts forecasts, optimism, and dispersion) tests, respectively, when we augment the respective regressions with our return comparability measures. Our predicted coefficients for return comparability are identical to those for earnings comparability because the arguments are the same. Before proceeding to the results, we note that untabulated analysis indicates earnings and return comparability are positively correlated. *Comp4 Ret* and *Comp4* (earnings) have a Pearson correlation coefficient of 0.31, while *CompInd Ret* and *CompInd* (earnings) have a Pearson correlation coefficient of 0.20. This positive correlation provides additional validation and comfort that earnings comparability is in part explained by economic comparability.

[Table 8]

In Table 8, we study the determinants of analyst following. We find that both proxies for return comparability are positively associated with analyst coverage. This finding is consistent with the idea that economic comparability across firms (in this case reflected in returns) is associated with richer information sets, which leads to higher analyst coverage. Perhaps more interestingly, earnings comparability continues to be positively associated with analyst coverage. Table 9 presents the results for the forecast properties. We find that return comparability is positively associated with analyst forecast accuracy and negatively associated with analyst forecast bias. Also, consistent with table 7, we do not find a statistical relation between return comparability and analyst forecast dispersion. Last, we show that the effect of earnings comparability on analyst forecast accuracy and bias is robust to the inclusion of return comparability.

[Table 9]

The Tables 8 and 9 results suggest that the effect of earnings comparability is incremental to the effect of return comparability in determining analyst coverage and in assisting analysts to produce more accurate and less optimistically-biased earnings forecasts. These results are consistent with the existence of a multiple dimensions of comparability, perhaps an economic dimension that captures both long-term cash flow expectations and growth options as well as a near-term, accounting-oriented dimension. It is also possible that both variables are measuring a single underlying comparability construct with error.

6. Conclusion

This paper first develops a firm-year measure of earnings comparability and then studies the capital market consequences of this comparability measure. A key innovation is the development of an empirical, firm-specific, output-based, quantitative measure of earnings comparability. It is based on the strength of the historical covariance between a firm's earnings and the earnings of other firms in the same industry. We provide construct validity of our measure. We find that the likelihood of an analyst using firm *j* as a benchmark when analyzing firm *i* in a report is *increasing* in the relative earnings comparability between firm *i and j*, as defined using our measure.

We test whether earnings comparability affects analyst coverage and properties of analyst forecasts as a proxy for the firm's information environment. With respect to analyst coverage, we find that coverage is increasing in comparability. Tests also indicate that the likelihood of an analyst covering firm *i* also covering firm *j* is *increasing* in the relative earnings comparability between firm *i and j*. Hence we not only show that earnings comparability leads to greater analyst following, but also specifically predict which other firms an analyst will follow. These results are consistent with earnings comparability leading to richer information sets, which more than offsets the potential decreased benefit due to reduced investor demand for information about high-comparability firms. In addition, we also find that analysts who follow firms with higher earnings comparability issue more accurate and less biased earnings forecasts. These results suggest that earnings comparability helps analysts to forecast earnings and that the improvement comes, at least in part, through a reduction in forecast optimism. Additional analysis suggests that earnings comparability, while positively correlated with, is not subsumed by, an analogous measure of return comparability.

In sum, we develop a measure of earnings comparability that likely captures user's notions of comparability and the benefits of comparability to them. We document tangible benefits for firms with higher comparability, such as improved analyst coverage, and benefits for users of financial statements issued by more comparable firms, such as improved forecasting. While comparability is generally and widely accepted as a valuable trait, there is little evidence beyond this study proving this. With some (yet-to-be-designed) modifications, we believe our comparability measure could be used: to evaluate whether an action achieves the intended consequence of enhanced comparability (e.g., issuance of a new standard, effect of accounting adjustments); to help researchers design more powerful tests (via better matching); and, to assist practitioners in choosing comparable firms.

Not withstanding the above benefits, some caveats are in order. We do not study the determinants of earnings comparability. We are agnostic about the role of comparable economics versus comparable accounting in explaining our measure, and hence about their roles in driving the benefits we document in this study. Our analysis is silent on what firms can do to improve cross-sectional comparability. On one hand, certainly, firm could choose to have more comparable accounting (and certainly there is demand from accounting researchers to isolate and measure accounting comparability). On the other hand, we speculate that economic innovations, which by definition distinguish firms from their peers, could lead to decreased economic comparability. In addition, while earnings is arguably the most important summary measure of accounting performance, it captures only one financial-statement dimension. An opportunity exists to create a multi-dimensional financial statement measure. We leave these issues to future research.

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APPENDIX
Variable Definitions

Variable	Definition
ijRSQ	= R^2 from a regression of firm *i*'s annual earnings on the annual earnings of firm *j*. It is calculated for each firm *i* – firm *j* pair, ($i \neq j$), j = 1 to *J* firms in the same 2-digit SIC industry as firm *i*.
Comp4	= Average of the four highest *ijrsq* for firm *i*.
CompInd	= Average *ijrsq* for firm *i* for all firms in the industry.
Comp4 Ret	= Average of the four highest *ijrsq* for firm *i* from a regression of firm *i* return on firm *j* return.
CompInd Ret	= Average *ijrsq* for firm *i* for all firms in the industry from a regression of firm *i* return on firm *j* return.
Coverage-N	= Number of analysts issuing a forecast for the firm.
Coverage	= Logarithm of the number of analysts issuing a forecast for the firm.
CondCoverage	= Indicator variable that equals one if analyst *k* who *covers* firm *i* also covers firm *j*, and equals zero otherwise. An analyst "covers" a firm if she issues at least one annual forecast about the firm.
UseAsComp	= Indicator variable that equals one if analyst *k* who *writes a report* about firm *i* refers to firm *j* as a comparable firm in her report, and equals zero otherwise.
Accuracy	= Absolute value of the forecast error multiplied by -1, scaled by the stock price at the end of the prior fiscal year, where the forecast error is the I/B/E/S analysts' mean annual earnings forecast less the actual earnings as reported by I/B/E/S,.
Optimism	= Signed value of the forecast error, scaled by the stock price at the end of the prior fiscal year, where the forecast error is the I/B/E/S analysts' mean annual earnings forecast less the actual earnings as reported by I/B/E/S.
Dispersion	= Cross-sectional standard deviation of individual analysts' annual forecasts, scaled by the stock price at the end of the prior fiscal year.
Predictability	= R^2 of a regression of annual earnings on prior-year annual earnings for the same firm.
Size-$	= Market value of equity measured at the end of the year.
Size	= Logarithm of the market value of equity measured at the end of the year.
Book-Market	= Ratio of the book value to the market value of equity.
Volume	= Logarithm of trading volume in millions of shares during the year.
R&D	= Research and development expense scaled by total sales.
Depreciation	= Depreciation expense scaled by total sales.
Issue	= Indicator variable that equals one if the firm issues debt or equity securities during the preceding, current, or following year, and zero otherwise.
SUE	= Absolute value of unexpected earnings, scaled by the stock price at the end of the prior year, where unexpected earnings is actual earnings less a forecast based on a seasonal-adjusted random walk time-series model.
Neg UE	= Indicator variable that equals one if firm *i*'s earnings are below the reported earnings a year ago, and equals zero otherwise.
Loss	= Indicator variable that equals one if the current earnings is less than zero, and equals zero otherwise.
Neg SI	= Absolute value of the special item deflated by total assets if negative, and equals zero otherwise.
Days	= Logarithm of the number of days from the forecast date to the earnings announcement date.

TABLE 1
Descriptive statistics

This table provides descriptive statistics of *Comp4*, *CompInd*, and *Predictability* for the sample before (unrestricted) and after (analyst-restricted) we restrict it to firms with analyst coverage. Panel A presents the mean values of *Comp4* and *CompInd* by year of the observation for the pre- and post-analyst samples. Panel B provides descriptive statistics for the pre-analyst sample. Panel C shows the Pearson correlations for the pre-analyst sample. Variables are defined in the Appendix.

Panel A: Average comparability by year for the unrestricted and analyst-restricted samples

	Unrestricted Sample			Analyst-Restricted Sample		
Year	No. of Obs	*Comp4* (%)	*CompInd* (%)	Obs	*Comp4* (%)	*CompInd* (%)
1994	2,794	50.3	11.7	1,251	53.7	13.1
1995	2,941	50.9	11.9	1,332	53.8	13.1
1996	3,087	50.4	11.4	1,495	53.0	12.3
1997	3,580	52.2	11.3	1,774	54.1	11.9
1998	3,570	52.1	11.2	1,762	53.8	11.7
1999	3,723	52.2	11.0	1,759	54.0	11.4
2000	3,790	53.3	11.3	1,706	55.6	11.9
2001	3,733	53.5	11.4	1,698	55.7	12.1
2002	3,773	53.9	11.6	1,792	55.9	12.3
2003	3,932	54.5	11.4	1,977	56.8	12.1
2004	3,829	53.9	11.3	2,017	55.9	12.0
2005	3,584	53.6	11.6	1,945	55.0	12.2
Total	42,336	52.7	11.5	20,508	54.9	12.1

Panel B: Descriptive statistics for comparability and predictability for the unrestricted sample

Variable	No. of Obs	Mean	STD	10th Percent	Median	90th Percent
Comp4 (%)	42,336	52.7	15.7	32.5	52.4	73.6
CompInd (%)	42,336	11.5	5.4	6.2	10.3	18.3
Predictability (%)	42,336	15.9	21.2	0.2	6.5	47.6

Panel C: Correlations among the comparability and predictability measures for the unrestricted sample

	Comp4	*CompInd*	*Predictability*
Comp4	1.00	0.71	0.24
CompInd		1.00	0.37
Predictability			1.00

TABLE 2
Use of comparable firm in analysts' reports

This table reports an analysis of the relation between earnings comparability and analysts' use in their reports of firms in the same industry as the sample firm for the year 2005. The sample includes the combination of analysts reports about sample firms multiplied by the number of firms in each sample-firm's industry with available data. We estimate various specifications of the following pooled logistic regression:

$$UseAsComp_{ikj} = \alpha + \beta_1\, ijRSQ_{ij} + \gamma\, Controls_j + \varepsilon_{ikj}.$$

Industry fixed effects are included but not tabulated. Coefficient *z*-statistics are in parentheses. Significance levels are based on one-tailed tests where there is a prediction for the sign of the coefficient and based on two-tailed tests otherwise. ***, ** and * denotes significance at the 1%, 5% and 10% levels, respectively. Variables are defined in the Appendix.

	Prediction	(1)	(2)
ijRSQ	+	0.90***	0.76***
		(4.35)	(3.62)
Size	+	0.27***	0.30***
		(9.12)	(7.87)
Volume	+	0.22***	0.23***
		(6.67)	(6.29)
Book-Market	?	0.11*	0.22
		(1.72)	(1.58)
ROA	?	0.01	-0.02
		(0.07)	(0.03)
Size Difference	–		-0.42***
			(-10.79)
Volume Difference	–		-0.09***
			(-2.42)
Book-Market Difference	–		-0.32**
			(-2.06)
ROA Difference	–		-1.03**
			(-1.70)
Industry FE		Yes	Yes
Pseudo R^2		3.07%	3.83%
No. of Obs.		39,414	39,414

TABLE 3
Analyst coverage and earnings comparability: Descriptive statistics

This table reports descriptive statistics for the variables included in the analysis of the relation between earnings comparability and analyst coverage. The sample is restricted to observations with available data to calculate all the variables in this analysis. Panel A presents descriptive statistics and Panel B reports Pearson correlations.

Panel A: Descriptive statistics

Variable	No. of Obs	Mean	STD	10^{th} Percent	Median	90^{th} Percent
Coverage-N	18,735	7.0	6.9	1.0	4.0	18.0
Coverage	18,735	1.46	1.06	0.00	1.39	2.89
Comp4 (%)	18,735	54.9	14.6	35.6	54.8	74.7
CompInd (%)	18,735	12.1	5.2	6.6	10.9	19.0
Predictability (%)	18,735	16.1	20.4	0.3	7.1	48.5
Size-$M	18,735	2,720	7213	60	507	6,106
Log Size	18,735	6.35	1.87	4.04	6.23	8.81
Book-Market	18,735	0.54	0.39	0.15	0.47	0.97
Volume	18,735	1.99	1.85	-0.50	2.10	4.31
R&D	18,735	0.03	0.13	-0.05	0.00	0.13
Depreciation	18,735	0.00	0.05	-0.04	0.00	0.06
Issue	18,735	0.76	0.42	0.00	1.00	1.00

TABLE 3 (Continued)

Analyst coverage and earnings comparability: Descriptive statistics

Panel B: Correlation matrix

	Coverage	*Comp4*	*CompInd*	*Predictability*	*Size*	*Book-Market*	*Volume*	*R&D*	*Depreciation*	*Issue*
Coverage	1.00	0.03	0.09	0.05	0.76	-0.22	0.66	-0.06	0.10	0.05
		0.00	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*
Comp4		1.00	0.68	0.20	-0.01	-0.04	0.00	0.05	0.05	0.00
			<.0001	*<.0001*	*0.12*	*<.0001*	*0.71*	*<.0001*	*<.0001*	*0.56*
CompInd			1.00	0.33	0.04	0.07	-0.01	-0.07	0.05	-0.03
				<.0001	*<.0001*	*<.0001*	*0.23*	*<.0001*	*<.0001*	*<.0001*
Predictability				1.00	0.05	0.00	-0.04	-0.08	-0.04	-0.05
					<.0001	*0.62*	*<.0001*	*<.0001*	*<.0001*	*<.0001*
Size					1.00	-0.32	0.70	-0.11	0.04	0.04
						<.0001	*<.0001*	*<.0001*	*<.0001*	*<.0001*
Book-Market						1.00	-0.27	-0.19	0.00	-0.15
							<.0001	*<.0001*	*0.79*	*<.0001*
Volume							1.00	0.12	0.05	0.07
								<.0001	*<.0001*	*<.0001*
R&D								1.00	0.03	0.02
									<.0001	*0.02*
Depreciation									1.00	0.04
										<.0001
Issue										1.00

TABLE 4
Analyst coverage and earnings comparability: Multivariate tests

This table reports an analysis of the relation between earnings comparability and analyst coverage. The sample is restricted to observations with available data to calculate all the variables in this analysis. The table reports the results of various specifications of the following regression:

$$Coverage_{it+1} = \alpha + \beta_1\, Comparability_{it} + \beta_2\, Predictability_{it} + \gamma\, Controls_{it} + \varepsilon_{it+1}.$$

Industry and year fixed effects are included for each model but not tabulated. We estimate each model as a panel and cluster the standard errors at the firm level. Coefficient *t*-statistics are in parentheses. Significance levels are based on one-tailed tests where there is a prediction for the sign of the coefficient and based on two-tailed tests otherwise. ***, ** and * denotes significance at the 1%, 5% and 10% levels, respectively. Variables are defined in the Appendix.

	Prediction	(1)	(2)
Comp4	+	0.23***	
		(5.15)	
CompInd	+		0.65***
			(5.39)
Predictability	+	-0.02	-0.02
		(-0.50)	(-0.70)
Size	+	0.32***	0.32***
		(37.66)	(37.75)
Book-Market	–	0.12***	0.12***
		(5.72)	(5.70)
Volume	+	0.19***	0.19***
		(23.52)	(23.68)
R&D	+	0.01	0.01
		(0.10)	(0.08)
Depreciation	+	0.28**	0.27*
		(1.98)	(1.91)
Issue	+	0.03*	0.03*
		(1.89)	(1.85)
Industry and Year FE		Yes	Yes
R^2		71.1%	71.1%
No. of Obs.		18,735	18,735

TABLE 5
Analysts' coverage of comparable firms

This table reports an analysis of the relation between earnings comparability and analyst coverage of firms in the same industry as the sample firm. For each of the years 1994 to 2005 in our sample, we estimate the following logistic regression:

$$CondCoverage_{ikj} = \alpha + \beta_1\, ijRSQ_{ij} + \gamma\ Controls_j + \varepsilon_{ikj}.$$

Industry fixed effects are included but not tabulated. The number of observations used in the annual estimation is the combination of sample firms multiplied by the analysts covering the sample firms multiplied by the number of firms in each sample-firm's industry with available data. The table presents the mean, maximum, and minimum coefficients, pseudo R^2, and number of observations from the 12 annual logistic regressions. Mean coefficient *t*-statistics (in parentheses) are based on the distribution of the 12 annual coefficients and adjusted for time-series dependence using the Newey-West (1987) correction with one lag. Significance levels are based on one-tailed tests where there is a prediction for the sign of the coefficient and based on two-tailed tests otherwise. ***, **, and * denotes significance at the 1%, 5% and 10% levels, respectively. Variables are defined in the Appendix.

	Prediction	Mean (1)	Maximum (2)	Minimum (3)
ijRSQ	+	1.01***	1.32	0.78
		(25.41)		
Size	+	0.35***	0.50	0.21
		(11.97)		
Volume	+	0.25***	0.35	0.20
		(25.58)		
Book-Market	–	0.04***	0.15	0.00
		(2.12)		
R&D	+	0.21**	0.95	-0.05
		(1.97)		
Depreciation	+	0.62***	1.76	0.02
		(4.33)		
Issue	+	0.01	0.14	-0.15
		(0.44)		
Industry FE		Yes		
Pseudo R^2		5.97%	9.50%	4.41%
No. of Obs.		2,904,641	4,133,881	1,441,881

TABLE 6
Analyst forecasts properties and earnings comparability: Descriptive statistics

This table reports descriptive statistics for the variables included in the analysis of the relation between earnings comparability and the properties of analysts' forecasts. The sample is restricted to observations with available data to calculate all the variables in this analysis. Panel A presents descriptive statistics and Panel B reports Pearson correlations.

Panel A: Descriptive statistics

Variable	No. of Obs	Mean	STD	10^{th} Percent	Median	90^{th} Percent
Accuracy	17,178	-0.04	0.12	-0.09	-0.01	0.00
Optimism	17,014	0.03	0.11	-0.02	0.00	0.07
Dispersion	11,405	0.01	0.02	0.00	0.00	0.02
Comp4	17,178	54.8	14.5	35.6	54.7	74.7
CompInd	17,178	12.1	5.1	6.6	10.9	19.0
Predictability	17,178	16.1	20.4	0.3	7.1	48.5
SUE	17,178	1.40	4.55	0.02	0.26	2.98
Neg UE	17,178	0.38	0.49	0.00	0.00	1.00
Loss	17,178	0.24	0.43	0.00	0.00	1.00
Neg SI	17,178	0.01	0.05	0.00	0.00	0.01
Days	17,178	5.92	0.21	5.89	5.95	6.02

TABLE 6 (Continued)
Analyst forecasts properties and earnings comparability: Descriptive statistics

Panel B: Correlation matrix

	Accuracy	*Optimism*	*Dispersion*	*Comp4*	*CompInd*	*Predictability*	*SUE*	*Neg UE*	*Loss*	*Neg SI*	*Days*
Accuracy	1.00	-0.94	-0.46	0.04	0.03	0.05	-0.06	-0.11	-0.25	-0.06	-0.06
		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Optimism		1.00	0.35	-0.04	-0.04	-0.03	0.02	0.12	0.20	0.05	0.06
			<.0001	<.0001	<.0001	0.00	0.00	<.0001	<.0001	<.0001	<.0001
Dispersion			1.00	-0.01	-0.01	-0.09	0.09	0.17	0.38	0.07	0.17
				0.25	0.23	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Comp4				1.00	0.68	0.20	-0.01	-0.02	0.01	0.01	-0.01
					<.0001	<.0001	0.11	0.04	0.50	0.27	0.45
CompInd					1.00	0.33	-0.02	-0.03	-0.06	-0.02	0.03
						<.0001	0.03	0.00	<.0001	0.02	<.0001
Predictability						1.00	-0.06	-0.05	-0.08	-0.02	0.02
							<.0001	<.0001	<.0001	0.04	0.00
SUE							1.00	0.02	0.15	0.15	0.01
								0.02	<.0001	<.0001	0.10
Neg UE								1.00	0.39	0.14	0.03
									<.0001	<.0001	0.00
Loss									1.00	0.20	0.05
										<.0001	<.0001
Neg SI										1.00	0.02
											0.01
Days											1.00

TABLE 7
Analyst forecasts properties and earnings comparability: Multivariate tests

This table reports an analysis of the relation between earnings comparability and the properties of analysts' forecasts. The sample is restricted to observations with available data to calculate all the variables in this analysis. The table reports the results of various specifications of the following regression:

$$Forecast\ Metric_{it+1} = \alpha + \beta_1\ Comparability_{it} + \beta_2\ Predictability_{it} + \gamma\ Controls_{it} + \varepsilon_{it+1}.$$

Forecast Metric is *Accuracy*, *Optimism* or *Dispersion*. Industry and year fixed effects are included for each model but not tabulated. We estimate each model as a panel and cluster the standard errors at the firm level. Coefficient *t*-statistics are in parentheses. Significance levels are based on one-tailed tests where there is a prediction for the sign of the coefficient and based on two-tailed tests otherwise. ***, ** and * denotes significance at the 1%, 5% and 10% levels, respectively. Variables are defined in the Appendix.

	Forecast Metric = Accuracy			*Forecast Metric = Optimism*			*Forecast Metric = Dispersion*		
	Prediction	(1)	(2)	Prediction	(3)	(4)	Prediction	(5)	(6)
Comp4	+	0.017**		–	-0.017**		–	0.001	
		(2.29)			(-2.48)			(0.66)	
CompInd	+		0.036**	–		-0.053***	–		0.004
			(2.08)			(-3.14)			(1.60)
Predictability	+	0.015***	0.015***	–	-0.008	-0.007	–	-0.003**	-0.003***
		(2.87)	(2.92)		(-1.56)	(-1.36)		(-4.68)	(-4.99)
SUE	–	-0.001*	-0.001*	?	0.000	0.000	+	0.000**	0.000**
		(-1.95)	(-1.93)		(0.40)	(0.38)		(2.39)	(2.40)
Neg UE	–	-0.002	-0.002	+	0.008***	0.008***	?	0.000	0.000
		(-1.25)	(-1.23)		(4.28)	(4.26)		(0.59)	(0.60)
Loss	–	-0.066***	-0.066***	+	0.049***	0.049***	+	0.012***	0.012***
		(-16.78)	(-16.78)		(13.38)	(13.37)		(18.96)	(18.99)
Neg SI	–	-0.003	-0.002	+	-0.008	-0.009	?	-0.006	-0.006
		(-0.10)	(-0.07)		(-0.31)	(-0.35)		(-0.91)	(-0.91)
Days	–	-0.027***	-0.027***	+	0.027***	0.028***	+	0.022***	0.022***
		(-7.32)	(-7.34)		(7.46)	(7.50)		(4.68)	(4.69)
Industry and Year FE		Yes	Yes		Yes	Yes		Yes	Yes
R^2		9.80	9.79		8.15	8.16		20.9	20.9
No. of Obs.		17,178	17,178		17,014	17,014		11,405	11,405

TABLE 8
Analyst coverage tests: Earnings and return comparability

This table reports an analysis that is identical to that in Table 4 but includes a measure of return comparability. The sample is restricted to observations with available data to calculate all the variables in this analysis. The table reports the results of various specifications of the following regression:

$$Coverage_{it+1} = \alpha + \beta_1\, Comparability_{it} + \beta_2\, Predictability_{it} + \gamma\, Controls_{it} + \varepsilon_{it+1}.$$

Comparability includes measures based on both earnings and return historical covariances. Industry and year fixed effects are included for each model but not tabulated. We estimate each model as a panel and cluster the standard errors at the firm level. Coefficient *t*-statistics are in parentheses. Significance levels are based on one-tailed tests where there is a prediction for the sign of the coefficient and based on two-tailed tests otherwise. ***, ** and * denotes significance at the 1%, 5% and 10% levels, respectively. Variables are defined in the Appendix.

	Prediction	(1)	(2)
Comp4	+	0.180***	
		(3.82)	
Comp4 Ret	+	0.709***	
		(9.38)	
CompInd	+		0.503***
			(4.09)
CompInd Ret	+		1.395***
			(6.53)
Predictability	+	-0.015	-0.013
		(-0.15)	(-0.37)
Size	+	0.311***	0.326***
		(35.80)	(36.36)
Book-Market	–	0.091***	0.107***
		(4.08)	(4.31)
Volume	+	0.188***	0.185***
		(21.23)	(21.89)
R&D	+	-0.081	-0.060
		(-1.17)	(-0.88)
Depreciation	+	0.382**	0.375**
		(2.54)	(2.46)
Issue	+	0.046**	0.032**
		(2.44)	(2.18)
Industry and Year FE		Yes	Yes
R^2		71.7%	71.7%
No. of Obs.		16,603	16,603

TABLE 9
Analyst forecasts properties tests: Earnings and return comparability

(Table description follows)

	Forecast Metric = Accuracy			*Forecast Metric = Optimism*			*Forecast Metric = Dispersion*		
	Prediction	(1)	(2)	Prediction	(3)	(4)	Prediction	(5)	(6)
Comp4	+	0.013*		–	-0.012*		–	0.001	
		(1.66)			(-1.64)			(0.91)	
Comp4 Ret	+	0.063***		–	-0.054***		–	0.001	
		(6.91)			(-6.56)			(0.34)	
CompInd	+		0.031*	–		-0.042**	–		0.004
			(1.65)			(-2.35)			(1.43)
CompInd Ret	+		0.172***	–		-0.179***	–		0.003
			(6.42)			(-7.14)			(0.78)
Predictability	+	0.013**	0.013**	–	-0.006	-0.005	–	-0.003***	-0.003***
		(2.24)	(2.29)		(-1.13)	(-1.00)		(-4.61)	(-4.78)
SUE	–	0.000*	0.000	**?**	0.000	0.000	+	0.000**	0.000**
		(-1.64)	(-1.54)		(0.35)	(0.43)		(2.01)	(2.00)
Neg UE	–	-0.002	-0.002	+	0.008***	0.008***	**?**	0.000	0.000
		(-1.03)	(-1.05)		(3.97)	(4.05)		(-0.27)	(0.15)
Loss	–	-0.068***	-0.068***	+	0.050***	0.051***	+	0.012***	0.012***
		(-15.41)	(-15.34)		(12.43)	(12.50)		(17.80)	(17.57)
Neg SI	–	-0.006	-0.001	+	-0.011	-0.018	**?**	-0.005	-0.004
		(-0.24)	(-0.05)		(-0.39)	(-0.65)		(-0.81)	(-0.67)
Days	–	-0.027***	-0.028***	+	0.029***	0.029***	+	0.022***	0.020***
		(-6.97)	(-7.03)		(7.34)	(7.35)		(4.22)	(4.27)
Industry and Year FE		Yes	Yes		Yes	Yes		Yes	Yes
R^2		10.13	10.06		8.47	8.53		21.0	20.8
No. of Obs.		15,218	15,218		15,082	15,082		10,238	10,238

TABLE 9 (Continued)
Analyst forecasts properties tests: Earnings and return comparability

This table reports an analysis that is identical to that in Table 7 but includes a measure of return comparability. The sample is restricted to observations with available data to calculate all the variables in this analysis. The table reports the results of various specifications of the following regression:

$$Forecast\ Metric_{it+1} = \alpha + \beta_1\ Comparability_{it} + \beta_2\ Predictability_{it} + \gamma\ Controls_{it} + \varepsilon_{it+1}.$$

Forecast Metric is *Accuracy*, *Optimism* or *Dispersion*. *Comparability* includes measures based on both earnings and return historical covariances. Industry and year fixed effects are included for each model but not tabulated. We estimate each model as a panel and cluster the standard errors at the firm level. Coefficient *t*-statistics are in parentheses. Significance levels are based on one-tailed tests where there is a prediction for the sign of the coefficient and based on two-tailed tests otherwise. ***, ** and * denotes significance at the 1%, 5% and 10% levels, respectively. Variables are defined in the Appendix.