The Benefits of Financial Statement Comparability

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ABSTRACT

Investors, regulators, academics, and researchers all emphasize the importance of financial statement comparability. However, an empirical construct of comparability is typically not specified. In addition, little evidence exists on the benefits of comparability to users. This study attempts to fill these gaps by developing a measure of financial statement comparability. Empirically, this measure is positively related to analyst following and forecast accuracy, and negatively related to analysts' dispersion in earnings forecasts. These results suggest that financial statement comparability lowers the cost of acquiring information, and increases the overall quantity and quality of information available to analysts about the firm.

The Benefits of Financial Statement Comparability

1. *Introduction*

Several factors point toward the importance of "comparability" in regard to financial statement information across firms in financial analysis. According to the Securities and Exchange Commission (SEC) [2000], when investors judge the merits and *comparability* of investments, the efficient allocation of capital is facilitated and investor confidence nurtured. 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).[1] Financial statement analysis textbooks almost invariably stress the importance of comparability across financial statements in judging a firm's performance using financial ratios.[2] Despite the importance of comparability, however, a measure of financial statement comparability is not specified and there is little evidence of its benefits to financial statement users.

The term comparability in accounting textbooks, regulatory pronouncements, and academic research is defined in broad generalities rather than precisely. We focus on capturing the notion of *financial statement* comparability (hereafter comparability). As described in more

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[1] As an additional example of the importance of comparability in a regulatory context, comparability is 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.

[2] See, for example, Libby, Libby, and Short [2004, p. 707], Stickney, Brown, and Wahlen [2007, p. 199], Revsine, Collins, and Johnson [2004, pp. 213-214], Stickney and Weil [2006, p. 189], Wild, Subramanyam, and Halsey [2006, p. 31], Penman [2006, p. 324], White, Sondhi, and Fried [2002, p. 112], and Palepu and Healy [2007, p. 5-1].

detail in section 2, we build our definition of comparability on the idea that the accounting system is a mapping from economic events to financial statements. For a given set of economic events, two firms have comparable accounting systems if they produce similar financial statements.

Because our comparability measure is new, we first study the properties of our measure as a function of firm economic and earnings characteristics. We find that comparability is higher for firms in the same industry and for firms with similar market capitalization. Comparability is also higher for firms with similar earnings attributes such as accruals quality, earnings predictability, earnings smoothness, and whether or not the firm reports losses. Second, we study the construct validity of our measure via an analysis of the textual contents of a hand-collected sample of sell-side 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 – albeit modestly – in the comparability between the two firms. A one-standard-deviation increase in our comparability measure is associated with a 5% increase in the probability of being selected as a peer. This shows that our measure of comparability is related to the use of comparable firms in analysts' reports, bolstering the construct validity of our comparability metric.

We then document the benefits of comparability for sell-side analysts. For a given firm, we hypothesize that the availability of information about comparable firms lowers the cost of acquiring information, and increases the overall quantity and quality of information available about the firm. Our hypothesis is based in part on empirical evidence that suggests that analysts primarily interpret information as opposed to convey new information to the capital markets (e.g., Lang and Lundholm [1996]). We expect these features to result in more analysts covering

the firm. In addition, enhanced information should facilitate analysts' ability to forecast firm i's earnings, for example by allowing analysts to better explain firms' historical performance or to use information from comparable firms as additional input in their earnings forecasts. Thus we predict that comparability will be positively associated with forecast accuracy and negatively associated with forecast dispersion.

Consistent with the hypotheses, we find that analyst following is modestly increasing in comparability. Specifically, the likelihood that an analyst who is covering a particular firm (e.g., firm i) would also be covering another firm in the same industry (e.g., firm j) is increasing in the comparability between the two firms. A one-standard-deviation increase in our comparability measure results in a 1% to 3% increase in the probability of being selected as a peer. Further, firms classified as more comparable are also covered by more analysts (by 0.5 more analysts on average). These results suggest that analysts indeed benefit, i.e., face lower information acquisition and processing costs, from higher comparability.

We also find that comparability is positively associated with analyst forecast accuracy and negatively associated with forecast dispersion. As for forecast accuracy, in terms of economic significance, a one-standard-deviation change in our comparability measure is associated with an improvement in accuracy of about 23%. Further, the correlation between analysts' forecast errors of two firms is increasing in the comparability between the two firms. This suggests that when attributes of financial reporting are common across firms, the sign and magnitude of analyst forecast errors are likely to become more systematic. As for forecast dispersion, a one-standard-deviation change in our comparability measure results in a reduction in forecast dispersion of 27%. This finding is consistent with the availability of superior public

information about highly comparable firms and an assumption that analysts use similar forecasting models.

Our study contributes to the literature in two ways. First, we develop an empirical measure of financial statement comparability intended to capture comparability from the perspective of users, such as analysts, who evaluate historical performance and forecast future firm performance or who make other decisions using financial statement information. While our primary focus is on developing a comparability measure at the firm level, we also construct 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 of financial statement comparability is firm-specific, output-based, and quantitative. It is calculated using widely available financial statement and return data. This measure contrasts with qualitative input-based definitions of comparability, such as business activities or accounting methods. Using these input-based measures can be challenging because researchers must decide which accounting choices to use, how to weight them, how to account for variation in their implementation, etc. In addition, it is often difficult (or costly) to collect data on a broad set of accounting choices for a large sample of firms.

Second, we provide evidence of the benefits of comparability to analysts. The ability to forecast future earnings is a common task for users, who are broadly defined to include not only analysts but also investors, particularly those engaged in valuation. Improved accuracy, for example, represents a tangible benefit to this user group. These findings are consistent with the results in concurrent work by Bradshaw, Miller and Serafeim [2009], who examine the relation between accounting method heterogeneity and analysts' forecast accuracy and dispersion. While comparability is generally accepted as a valuable attribute to users, little evidence exists beyond

these studies that would empirically confirm this belief.

Two caveats are in order. First, while our empirical strategy attempts in several ways to mitigate endogeneity concerns, we cannot rule out the possibility that some omitted variable (e.g., firm innovation) causes both a lack of comparability and a poorer information environment. In addition, as opposed to comparability causing analysts' actions, as we imply in our analysis, a reverse causality is also possible in that analysts pressure firms to choose more comparable accounting methods. For example, Jung [2010] argues and provides evidence that demand for more comparable firm disclosures by institutions, and by the buy-side analysts they employ, is greater among firms that have overlapping institutional ownership.

Second, our empirical measure of comparability relies on reported earnings as a key financial reporting metric. This is not to say that earnings is the only important metric. In fact, for several stakeholders such as lenders, credit ratings agencies, or regulators, balance sheet items are also important. Using a single financial statement measure, however, allows our analysis to be both parsimonious and tractable. As part of our analysis, we discuss potential limitations and develop alternative specifications for our comparability measure. We find that our results are robust to these alternative approaches.

The next section defines our measures of financial statement comparability. Section 3 outlines our hypotheses that comparability provides benefits to analysts. We provide descriptive statistics and construct validity tests of our measures in section 4. Section 5 presents the results of our empirical tests. The last section concludes.

2. *Empirical Measures of Comparability*

In the following subsections, we conceptually define financial statement comparability, explain how we compute our empirical measure of comparability, and, finally, discuss the

measure in the context of the extant literature.

2.1 CONCEPTUAL DEFINITION OF FINANCIAL STATEMENT COMPARABILITY

FASB [1980] states that, "comparability is the quality of information that enables users to identify similarities and differences between two sets of economic phenomena." We add structure to this idea by defining the accounting system as a mapping from economic events to financial statements. As such, it can be represented as follows:

$$Financial\ Statements_i = f_i(Economic\ Events_i) \tag{1}$$

where $f_i(\ )$ represents the accounting system of firm i. Two firms have comparable accounting systems if their mappings are similar.

Equation 1 states that a firm's financial statements are a function of the economic events and of the accounting of these events. Following this logic we conceptually define financial statement comparability as follows:

Two firms have comparable accounting systems if, for a given set of economic events, they produce similar financial statements.

That is, two firms, i and j, with comparable accounting should have similar mappings $f(\bullet)$, such that for a given a set of economic events X, firm j produces similar financial statements to firm i.

2.2 EMPIRICAL MEASURE OF FINANCIAL STATEMENT COMPARABILITY

To put our conceptual definition of comparability into practice, we develop a simple empirical model of the firm's accounting system. (We discuss variations of this measure in section 5.3) In the context of equation 1, consistent with the empirical financial accounting literature (see Kothari [2001]), we use stock return as a proxy for the net effect of economic events on the firm's financial statements. These economic events could be unique to the firm but could also be due to industry- or economy-wide shocks. Our proxy for financial statements is

earnings. While earnings is certainly one important summary income statement measure, we acknowledge that using only earnings to capture financial statement comparability is a limitation of our analysis. For each firm-year we first estimate the following equation using the 16 previous quarters of data:

$$Earnings_{it} = \alpha_i + \beta_i\ Return_{it} + \varepsilon_{it} \tag{2}$$

Earnings is the ratio of quarterly net income before extraordinary items to the beginning-of-period market value of equity, and *Return* is the stock price return during the quarter. Under the framework in equation 1, $\hat{\alpha}_i$ and $\hat{\beta}_i$ proxy for the accounting function *f(•)* for firm *i*. Similarly, the accounting function for firm *j* is proxied by $\hat{\alpha}_j$ and $\hat{\beta}_j$ (estimated using the earnings and return for firm *j*).

The "closeness" of the functions between two firms represents the comparability between the firms.   To estimate the distance between functions, i.e., a measure of closeness or comparability, we invoke one implication of accounting comparability: if two firms have experienced the *same* set of economic events, the more comparable the accounting between the firms, the more similar their financial statements. We use firm *i*'s and firm *j*'s estimated accounting functions to predict their earnings, assuming they had the same return (i.e., if they had experienced the same economic events, *Return_{it}*). Specifically, we use the two estimated accounting functions for each firm with the economic events of *a single* firm. We calculate:

$$\mathrm{E}(Earnings)_{iit} = \hat{\alpha}_i + \hat{\beta}_i\ Return_{it} \tag{3}$$

$$\mathrm{E}(Earnings)_{ijt} = \hat{\alpha}_j + \hat{\beta}_j\ Return_{it} \tag{4}$$

$\mathrm{E}(Earnings)_{iit}$ is the predicted earnings of firm *i* given firm *i*'s function and firm *i*'s return in period *t*; and, $\mathrm{E}(Earnings)_{ijt}$ is the predicted earnings of firm *j* given firm *j*'s function and firm *i*'s return in period *t*. By using firm *i*'s return in both predictions, we explicitly hold the economic

events constant.

We define accounting comparability between firms i and j ($CompAcct_{ijt}$) as the negative value of the average absolute difference between the predicted earnings using firm i's and j's functions:

$$CompAcct_{ijt} = -1/16 * \sum_{t-15}^{t} | E(Earnings_{iit}) - E(Earnings_{ijt}) | \qquad (5)$$

Greater values indicate greater accounting comparability. We estimate accounting comparability for each firm i – firm j combination for J firms within the same SIC 2-digit industry classification and whose fiscal year ends in March, June, September, or December.[3] In addition to the $i - j$ measure of comparability, we also produce a firm-year measure of accounting comparability by aggregating the firm i – firm j $CompAcct_{ijt}$ for a given firm i. Specifically, after estimating accounting comparability for each firm i – firm j combination, we rank all the J values of $CompAcct_{ijt}$ for each firm i from the highest to lowest. $CompAcct4_{it}$ is the average $CompAcct_{ijt}$ of the four firms j with the highest comparability to firm i during period t.[4] Similarly, $CompAcctInd_{it}$ is the median $CompAcct_{ijt}$ for all firms j in the same industry as firm i during period t. Firms with high $CompAcct4$ and $CompAcctInd$ have accounting functions that are more similar to those in the peer group and in the industry, respectively.

2.3   DISCUSSION OF THE COMPARABILITY MEASURE

Our comparability measure is related to other measures used in the extant literature. Prior

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[3] We exclude holding firms. Compustat contains financial statements for both the parent and subsidiary company, and we want to avoid matching two such firms. We exclude ADRs and limited partnerships because our focus is on corporations domiciled in the United States. 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. We also exclude firms with names that are 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.

[4] 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 *CompAcct10* from the average *CompAcct_{ij}* from the top-ten firms. The results are similar to using the top-four firms.

research has examined comparable *inputs* such as similar accounting methods. For example, Bradshaw and Miller [2007] study whether international firms that intend to harmonize their accounting with U.S. GAAP adopt U.S. GAAP accounting methods. DeFond and Hung [2003] argue that accounting choice heterogeneity (e.g., differences in LIFO versus FIFO inventory methods) increases the difficulty in comparing earnings across firms. Bradshaw, Miller and Serafeim [2009] define accounting heterogeneity based on whether accounting methods are atypical in an industry.

In contrast to these studies, in developing our measures we focus on earnings, a financial statement *output*. Our output-based method has a number of advantages over an input-based method. First, a measure of comparability based on firms' accounting choices faces several challenges: which choices to use, how to weight them, how to account for variation in their implementation, etc. In constructing a measure, a researcher must consequently make difficult (and somewhat ad hoc) decisions. In contrast, our methodology abstracts these challenges and instead employs the actual weights firms use when computing reported earnings. Second, for a given economic event, firms that use the same accounting inputs will produce the same output. However, it is possible that two firms with different accounting inputs might still produce the same output (e.g., LIFO versus FIFO when prices and inventory levels are constant). From the user's perspective, this lack of input comparability is not relevant and is not reflected in our measures. Finally, as a practical matter, it is often hard (or costly) to collect data on a broad set of accounting choices for a large sample of firms. In contrast, our measures are calculated using widely available financial statement and return data.

Other existing measures of comparability are based mainly on similarities in cross-sectional levels of contemporaneous measures (e.g., return on equity, firm size, price multiples)

at a single point in time and designed to measure differences across countries (e.g., Joos and Lang [1994], Land and Lang [2002]). Our measures are dynamic, capturing similarities over time, and are firm-specific. Our measure is also different from commonly studied earnings attributes, such as accrual quality, predictability, smoothness, etc. These attributes are firm-specific and calculated independently of the attributes of other firms. As the FASB [1980] points out, "Comparability is…a quality of the relationship between two or more pieces of information." Thus, if our measure captures comparability, we would expect our measure to be related to *similarities* in attributes across firms. (We conduct such an analysis in section 4.1 and find support for this conjecture.)

3. *Hypotheses: The Effect of Comparability on Analysts*

In this section, we develop hypotheses at the firm level about the effect of comparability on analysts and therefore on the properties of their forecasts. Tests of these hypotheses are also at the firm level, although we do conduct some complementary tests at the firm i − firm j level.

Any lesson on financial statement analysis emphasizes the difficulty in drawing meaningful economic comparisons from a financial measure unless there is a "comparable" benchmark. FASB [1980, p. 40] echoes this point. Implicit is the idea that by making sharper inferences about economic similarities and differences across comparable firms, the analyst is in a better position to understand and predict economic events. More comparable firms constitute better benchmarks for each other. In addition, information transfer among comparable firms should also be greater. Studies by Ramnath [2002], Gleason, Jenkins, and Johnson [2008], Durnev and Mangen [2009] among others, document the effect of one firm's financial statement information on the financial statements and operating decisions of other related firms. The net result is a set of higher quality information for more comparable firms.

Based on the above arguments, we expect the effort exerted by analysts to understand and analyze the financial statements of firms with comparable peers to be lower than their effort for firms without comparable peers. As a result of this difference in analysts' cost of analyzing a firm, we investigate variation in two dimensions of analysts' behavior – the number of analysts following a firm and the properties of analysts' forecasts.

Our first hypothesis examines whether financial statement comparability enhances analyst coverage. As discussed in Bhushan [1989] and in Lang and Lundholm [1996], the number of analysts following a firm is a function of analysts' costs and benefits. We argue that, ceteris paribus, since the cost to analyze firms that have other comparable firms is lower, more analysts should cover these firms. Hypothesis 1 (in alternate form) is:

> *H1*: Ceteris paribus, financial statement comparability is positively associated with analysts' coverage.

The null hypothesis is that the better information environment associated with higher-comparability firms will decrease investor demand for analyst coverage. That is, the benefits to analysts will decrease as well. However, the literature on analysts suggests that they 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]). Further, Lang and Lundholm [1996] and others 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 support our signed prediction.

Our second set of hypotheses examines the relation between comparability and the properties of analysts' earnings forecasts. The first property we examine is forecast accuracy.

As mentioned above, we expect firms with higher comparability to have higher quality information sets. Higher comparability could allow analysts to better evaluate firms' historical and current economic performance. Analysts could also better understand how economic events translate into accounting performance for higher comparability firms. This enhanced knowledge facilitates analysts' ability to forecast firm $i's$ earnings and thus leads to improved forecast accuracy. Hypothesis 2a (in alternative form) is:

> *H2a*: Ceteris paribus, financial statement comparability is positively associated with analysts' forecast accuracy.

In support of the null of H2a, if information at comparable firms is noisy or biased, then increased comparability could lead to less accurate forecasts. We expect this effect to reduce our tests' ability to provide support for this prediction.

As our second prediction, we investigate the relation between comparability and analysts' 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 private information. This implies that comparability will reduce forecast dispersion. Hypothesis 2b (in alternative form) is:

> *H2b*: Ceteris paribus, financial statement comparability is negatively associated with analysts' forecast dispersion.

We acknowledge that superior public information via higher comparability could generate more dispersed forecasts, which would support the null of H2b. The intuition is that if some analysts process a given piece of information differently from other analysts, then the availability of greater amounts of public information for comparable firms could generate more highly dispersed forecasts. A number of theoretical studies predict such a phenomenon. Harris and Raviv [1993] and Kandel and Pearson [1995] develop models in which disclosures promote

a greater divergence in beliefs. Kim and Verrecchia [1994] allow investors to interpret firm disclosures differently, whereby better disclosure is associated with more private information production.[5]

4. *Estimating and Validating a Measure of Comparability*

4.1 DESCRIPTIVE ANALYSIS OF COMPARABILITY MEASURES

In this section we provide descriptive statistics for our *CompAcct* measure. We start with a description of the results from our estimation of equation 2, in which we regress earnings on returns for each firm in our sample on a yearly basis. Table 1 provides descriptive statistics for these regressions. The sample consists of 71,295 firm-years with available data to compute equation 2, irrespective of data availability for the other variables used throughout our tests. (Descriptive statistics are similar if we restrict the sample to those used in our tests.) The mean estimated β coefficient equals 0.02 and is consistent with a (weak) positive relation between earnings and return. The mean R^2 is 12%. Although not directly comparable, using a pooled regression with yearly data (as opposed to firm-specific regression with quarterly data), Basu (1997) estimates a β coefficient of 0.12 and an adjusted r-square of 10%.

[Table 1]

Next, given that our measure of *CompAcct* is new, we provide a series of benchmarks to evaluate it. Specifically, we randomly select a sample of *CompAcct* for the population of firm i - firm j pairs in the Compustat dataset and calculate the distribution of the measure. We then partition the dataset into sub-samples based on economic and earnings characteristics. The idea is that, while exploratory, this analysis can shed light on the determinants of cross-sectional

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[5] In untabulated analysis, we also test and find that analyst forecast optimism is decreasing in comparability. However, because the arguments behind this prediction are less clear than the ones with forecast accuracy and dispersion, we do not make a formal prediction about the relation between comparability and forecast optimism.

variation in our measure of comparability.

Our measure can be computed for any firm *i* - firm *j* pair in the Compustat universe. Due to the potential large number of pairs, we randomly select a sample of 10% of the available firm *i* – firm *j* pairs in the year 2005. Panel A of Table 2 presents descriptive statistics for *CompAcct* for this random sample of 635,777 firm *i* – firm *j* observations. The mean (median) value for *CompAcct* is -5.1 (-2.7), suggesting that the average (median) error in quarterly earnings between firm *i* and firm *j* functions is 5.1% (2.7%) of market value. The distribution of *CompAcct* is also left-skewed with large negative outliers.[6]

Next, we partition the sample by economic characteristics. We start with industry classification because this is a standard economic factor on which firms are often matched (e.g., Barber and Lyon [1996]). In addition, we also sort firms on size (i.e., market capitalization) and book-market to explore whether these factors explain the variation in our measure of comparability. We classify firm *i* and firm *j* on the basis of their respective firm characteristics (e.g., industry classification, size and book-market quintiles) and then compare similar firm *i* – firm *j* pairs (e.g., firms in the same industry or in the same size quintile) with opposite pairs (e.g., firms in different industries or in opposite size quintiles). The idea is to compare the values of *CompAcct* for firms that are expected to be comparable with those expected to be *not* comparable.

Panel B of Table 2 presents these results. In the case of industry, we start with all firm-pair observations in which firm *i* is in the banking industry as it is broadly defined (SIC 6000-6999). We then compare the values of *CompAcct* when firm *j* is in the manufacturing industry

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[6] In untabulated analysis we find some evidence that the skewness in *CompAcct* is greater for firms that are smaller, have lower book-to-market ratios (i.e., higher growth), have lower earnings predictability, and report a loss. Most of these variables are included in our tests as controls. In addition, to address this skewness issue, we re-estimate all regressions in our empirical analysis using a rank transformation of our measure of comparability converted into deciles. In all cases the results yield the same inference, both in economic and statistical terms.

(SIC 2000-3999), the utilities industry (SIC 4000-4999), and the banking industry. We expect the difference in economics between firm pairs to be greater when firms i and j are in different industries than when they are in the same industry. We use these particular industry comparisons because we expect differences to be more pronounced. The *CompAcct* metric behaves as we would presume. For example, the mean value of *CompAcct* is -2.7 when firms i and j are both banks, greater than (i.e., less negative than) the mean values of -4.2 and -4.1, when firm j is a manufacturing firm and a utility firm, respectively. This result supports the idea that our comparability measure is greater for firms that belong to the same industry.

In the case of size and book-market we compare firm-pair observations in which the firms i and j are in the most extreme quintiles of the respective factor. Specifically, we divide the firm-pair observations into quintiles based on firm i's factor. Similarly, we sort firm-pair observations based on firm j's factor. This creates 25 mutually exclusive partitions. We then compare firms in the same extreme quintiles (e.g., largest firms with largest firms or smallest firms with smallest firms) to firms in opposite extreme quintiles (e.g., largest firms with smallest firms, and vice-versa). When two firms are in the same extreme size quintile, the mean value of *CompAcct* (-5.6) is greater than it is for two firms in opposite extreme size quintiles (-6.7). The table also shows that the mean value of *CompAcct* for two firms in the same extreme book-market quintile (-6.0) is only slightly greater than it is for two firms in opposite extreme book-market quintiles (-6.1). One implication of these results is that economic similarities can affect our comparability measures, which in turn motivates us to control for industry, size, and book-market in our tests below.

As discussed in section 2, if our measure captures comparability, we would expect our measures to be related to *similarities* in earnings properties. We test this prediction by comparing

the value of *CompAcct* for firms with different levels of four earnings attributes commonly used in prior research—accrual quality, predictability, smoothness, and whether the firm reports a loss. *Accrual Quality* is the measure of accruals quality developed by Dechow and Dichev [2002] and used by Francis et al. [2005]. *Predictability* is the R^2 from a firm-specific AR1 model with 16 quarters of data (Francis et al. [2004]). *Smoothness* is the ratio of the standard deviation of earnings to the standard deviation of cash flows (Leuz, Nanda and Wysocki [2003], Francis et al. [2004]). *Loss* is an indicator variable that equals one if the current earnings is less than zero, zero otherwise (Dechow and Dichev [2002]). As before, for the first three earnings attributes, we sort firm-pair observations into 25 partitions based on firm-*i* and firm-*j* quintiles of the respective factor, and then compare the extreme quintile partitions in which the level of the factor is the same for firms *i* and *j*. For the *Loss* attribute, firm pairs are divided into four groups based on whether firms *i* or *j* had a loss.

Panel C of Table 2 presents these results. In the case of accruals quality, two firms with similar extreme quintiles of accrual quality have a mean value of *CompAcct* (-5.3) greater than the mean *CompAcct* value of two firms with opposite extreme quintiles of accrual quality (-6.1). While the magnitude of the difference varies, for each of the other three earnings attributes, the value of *CompAcct* between two firms with similar earnings attributes is greater than it is for two firms with dissimilar earnings attributes. In addition to providing benchmarks, these similarity-in-earnings-attribute results also provide evidence that our comparability measure behaves as one would expect, providing an implicit validation of the measure.

[Table 2]

4.2   VALIDATING OUR COMPARABILITY MEASURE

In this section, we test the construct validity of our comparability measure. The test

implicitly assumes that, for a given firm, analysts know the identity of comparable peer firms. This seems reasonable because analysts have access to a broad information set about each firm, which includes not only historical financial statements but also firms' business models, competitive positioning, markets, products, etc.

We make a testable prediction to provide construct validity for our measure of comparability. The prediction relates to the assumption underlying our measure that the relative ranking of firm i - firm j comparability identifies a set of peers that analysts view as comparable to firm i. We test this assumption using the choice of comparable firms in analyst's reports. The typical analyst report context is that the analyst desires to evaluate the current, or justify the predicted, firm valuation multiple (e.g., Price/Earnings ratio) using a comparative analysis of peers' valuation multiples as benchmarks. We assume that if an analyst issues a report about firm i, then we expect the analyst to be more likely to use peers that are "comparable" to firm i in her reports. We then predict that analysts' choice of peers will be correlated with our measure of comparability. Evidence of this prediction suggests that our measures of comparability are related to analysts' choice of comparable firms in their reports.

The comparable peers 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. Given the cost of collecting this information, we limit the analysis to one year of data. Firms in this sample (i.e., firms i) have a fiscal year end of December 2005. For these firms, we search Investext to find up to three reports per firm i, each written by a different analyst and each mentioning "comparable" or "peer" firms (i.e., potential firms j) in the report. We then record the name and ticker of all firms used by the analyst as a peer for firm i. We match these peers with Compustat using the firm

name and ticker. In total, we obtain 1,000 reports written by 537 unique analysts for 634 unique

firms i. Each report mentions one or more peers as comparable to the firm for which the analyst

has issued the report. The final sample for this test consists of 4,448 firms used as peers in the

analysts' reports.[7]

The "treatment" sample (i.e., when the dependent variable equals one) includes peers

chosen by analysts. We also require a sample of peers *not chosen* by analysts. We use two such

samples. First, for each analyst-chosen peer, we randomly select a peer from a pool of

companies with available data in the same 2-digit SIC (i.e., an industry-matched sample). In

addition, when using an industry-matched sample, we control for the *differences* in firm size and

book-market. Second, for all firms within the industry-matched sample, we select the firm with

the closest distance in size and book-market (i.e., an industry-, size-, and book-market-matched

sample). Specifically, we minimize the distance in size and book-market using the following

absolute percentage distance formula: $|(Size_i - Size_j) / Size_i| + |(Book\text{-}Market_i - Book\text{-}Market_j) /$

$Book\text{-}Market_i|$. These randomly chosen peers provide observations in which the dependent

variable equals zero. The number of analyst-chosen peers equals the number of matched peers

on a per firm basis. For example, if the analyst chooses 15 peers, then that analyst also has 15

matched control peers. The treatment sample consists of 4,947 firms used as peers in the

analysts' reports and 4,947 benchmark firms matched on either industry or industry, size and

book-market.

For our tests, we estimate the following Probit model:

$$AnalystComp_{ikj} = \alpha + \beta_1\, CompAcct_{ij} + \gamma\, Controls_j + \varepsilon_{ikj} \tag{6}$$

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[7] 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.

AnalystComp$_{ikj}$ 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, zero otherwise. *CompAcct$_{ij}$* is our measure of comparability. We predict that the probability of an analyst using firm *j* in her report is increasing in *CompAcct$_{ij}$*. To ease comparisons across coefficients, when estimating equation 6 we standardize all continuous variables to mean zero and unit variance. Instead of estimated coefficients, we report elasticities that can be interpreted as the change in probability of being selected as a peer for a one-standard-deviation change in the explanatory variable (or a unit-change for dummy variables). We include industry fixed effects at the 2-digit SIC industry classification. In addition, we cluster the standard errors at the firm *i* and analyst *k* levels (results are similar if we cluster at the analysts *k* and firm *j* levels instead).

We use *Size*, *Book-Market*, *Volume*, *ROA*, and industry fixed effects to control for variation in economic characteristics. Our choice of these controls follows their common usage by other researchers who match control firms with treatment firms along these dimensions (e.g., Barber and Lyon [1996, 1997], Kothari, Leone, and Wasley [2005]) or in models of peer choice (Bhojraj and Lee [2002]). Further, as discussed above, for the industry-matched sample we control for the differences in size and book-market between firms *i* and *j*, which are measured by the absolute value of the difference between firm *i*'s and firm *j*'s respective variables.

Throughout our tests we also control for earnings predictability (defined above) and the volatility of earnings and returns. *Volatility Earn* is the standard deviation of 16 quarterly earnings (deflated by total assets), consistent with the horizon used to estimate comparability. *Volatility Ret* is the standard deviation of monthly stock returns during the 48-month period used to estimate comparability. For some tests (e.g., forecast accuracy, described below), these variables have an established relation with the dependent variables. In other cases, these

variables represent natural controls, as our comparability measure is influenced by the volatility of earnings and returns.

Table 3 presents the regression results. In the first model, the benchmark sample is matched based on industry. The coefficient on comparability (*CompAcct*) is positive and statistically significant, suggesting that as comparability increases, the odds of an analyst using firm *j* as a peer in a report about firm *i* increases. The economic significance of these results, however, is modest. A one-standard-deviation increase in *CompAcct* results in a 5% increase in the probability of being selected as a peer. That is, the unconditional probability increases from 50% to 55%. As a benchmark, this effect is lower than the 12% probability increase of being selected a peer associated with a one-standard-deviation decrease in size difference.

In the second model, the benchmark sample is matched based on industry, size and book-market ratio. We use the same specification as in model 1 except we exclude variables that measure the differences in size and book-market ratios because observations were matched on these dimensions. (Untabulated analysis indicates that inferences are similar if we retain these variables in the model.) The coefficient on *CompAcct* is positive and statistically significant, although the economic significance is slightly reduced. A one-standard-deviation increase in *CompAcct* results in a 3% increase in the probability of being selected as a peer. Overall, the results in Table 3 support the notion that an analyst who writes a report about a firm more likely chooses benchmark peers that have higher values of comparability, after controlling for economic similarity. This bolsters the construct validity of our comparability measure.

[Table 3]

5.   *Empirical Tests*

5.1   CORRELATED ANALYST COVERAGE AND FORECAST ERRORS

In this section, continuing with our previous analysis in which we use pairwise firm i - firm j level comparability (as opposed to aggregated firm-i level comparability), we provide initial evidence of our hypotheses that higher comparability is positively related to analyst coverage and forecast accuracy.

Our first test is similar in spirit to the test in the previous section but now we use analysts' coverage choices instead of analysts' choices of comparable peers in their reports.[8] We expect that the likelihood that an analyst covering a particular firm (e.g., firm i) would also cover another firm in the same industry (e.g., firm j) increases in the comparability between these two firms. Hence, we not only predict that higher comparability leads to more analysts covering the firm (as we do in the next section); we also predict which other firms the analyst will follow.

We estimate the following pooled Probit model:

$$CondCoverage_{ikjt} = \alpha + \beta_1 \, CompAcct_{ijt} + \gamma \, Controls_{jt} + \varepsilon_{ikjt} \qquad (7)$$

CondCoverage is an indicator variable that equals one if analyst k who *covers* firm i also covers firm j, zero otherwise. An analyst "covers" a firm if she issues at least one annual forecast about the firm. *CompAcct* is our measure of comparability. We predict that the probability of covering firm j is increasing in *CompAcct* (i.e., $\beta_1 > 0$).

The pooled sample for this test is quite large. The sample consists of firm i – analyst k – firm j – year t observations available on IBES. For firm i, there are K analysts who cover the firm. For each firm i – analyst k pair, analyst k also covers J firms. Hence, our sample of

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[8] These tests of analyst coverage for the analysis in this section are not independent of the Table 3 tests of peers appearing in analyst reports. The use of a company as a peer in a report could partially be a result of the analyst covering that company, and vice versa. The overlap in samples, however, is small because we use the full sample for this analysis (i.e., Table 4) but only a year of data and about 600 firms for the analysis in Table 3.

observations in which *CondCoverage* equals one consists of *I* firms × *K* analysts × *J* firms × *T* years. As in Table 3, we match each of these analyst-chosen peers with an equal number of non-analyst chosen firms based on the same industry (industry-match) and the same industry with the closest size and book-market (industry-size-book-market match).[9] After matching each observation with a matched firm and requiring available data for the control variables, we are left with a sample of 2,147,780 observations (1,073,890 pairs) of firms matched on either industry or industry, size and book-market. As in the Table 3 analysis, instead of estimated coefficients, we report the change in probability of being selected as a peer for a one-standard-deviation change in the explanatory variable.

In estimating equation 7, 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], Barth, Kasznik, and McNichols [2001]). *Size* is the logarithm of the market value of equity measured at the end of the year. *Book-Market* is the ratio of the book value to the market value of equity. *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*, zero otherwise. *R&D* is research and development expense scaled by total sales. *Depreciation* is depreciation expense scaled by total sales. Following Barth, Kaznick and McNichols [2001], we industry adjust the R&D and depreciation measures by subtracting the respective 2-digit SIC industry mean value. Following the analysis in Table 3, we also control (in the industry-matched sample) for the differences in size and book-market

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[9] In addition to requiring valid data for all our measures, we require each analyst *k* to cover at least five firms. This restriction should exclude junior analysts, analysts in transition, and data-coding errors. We also exclude analysts who cover more than 40 firms. Covering more than 40 firms is rare (less than one percent of analysts) and could be a data-coding error in that the observations refer to the broker rather than to an individual analyst.

between firms i and j. We also include industry and year fixed effects at the 2-digit SIC industry classification and cluster the standard errors at the firm i and analyst k levels.

Table 4 presents the results. As in Table 3, in the first model the benchmark sample is matched based on industry, whereas in the second model it is matched based on industry, size and book-market ratios. In both models, the coefficient on *CompAcct* is positive and statistically significant, as predicted. These results suggest that the firms j we identify as "comparable" to firm i are more likely to be followed by the analysts who also cover firm i. The economic significance of these results, however, is modest. A one-standard-deviation increase in *CompAcct* results in a 3% increase in the probability of being selected as a peer in both models. The effects of the control variables on the probability of being selected as a peer are economically similar to those in Table 3. Overall, we find that the likelihood of an analyst covering firm j, conditional on the analyst covering firm i, increases in the comparability between firms i and j. This is consistent with higher comparability reducing the information acquisition and processing costs of covering the firm. It also suggests that the lower costs of covering firms with high comparability outweigh the potential decreased benefit from investors' reduced demand for analysts' information about highly comparable firms.

[Table 4]

As a second prediction at the firm i-j level, to the extent that accounting systems are more comparable, we expect the correlation between analyst forecast errors between firms i and j to increase. That is, increased comparability not only increases the ability of the analyst to learn about firm i from firm j, but also results in a situation where the deficiencies in financial reporting will be correlated. For example, both firms could have the same off-balance assets and liabilities, or fail to impair assets at the same time. Under these circumstances, the sign and

magnitude of the errors are likely to become more systematic. We test this notion using a similar set of independent variables but an alternative dependent variable, *CorrFcstError*, that proxies for the correlation in forecast errors across firms *i* and *j*. *CorrFcstError* is defined as:

$$CorrFcstError = |FcstError_{it} - FcstError_{jt}| \times -1 \tag{8}$$

FcstError is I/B/E/S analysts' mean annual earnings forecast less the actual earnings as reported by I/B/E/S, scaled by the stock price at the end of the prior fiscal year, calculated separately for firms *i* and *j*. We multiply the difference by -1 so that higher values are associated with higher correlations between firms *i* and *j* forecast errors. This measure will also be greater when the magnitudes of forecast errors in general are smaller. Our firm-*j* level independent variables should be correlated with and hence control for this forecast error magnitude. Consistent with the tests on conditional analyst coverage, the sample for these tests is restricted to pairs of firms *i-j* observations in which analysts cover both firms, and enough information is available to calculate each forecast error. The regression specification also follows equation 7 except that we estimate OLS regressions (as opposed to Probit regressions) because the dependent variable is continuous.

The results are presented in Column 3 of Table 4. The coefficient on comparability is positive, consistent with our prediction that analyst forecast errors become more systematic across firms as comparability increases between them. In terms of economic significance a one-standard-deviation change in *CompAcct* results in an increase in the dependent variable of 0.34 (the explanatory variables in Table 4 are standardized to facilitate interpretation of coefficients). Given that the mean value for *CorrFcstError* (untabulated) equals 0.61, this represents an increase of 56%. The coefficients for the control variables generally obtain the predicted signs. For example, *CorrFcstError* is greater when firm *j*'s are larger in size and have more predictable earnings. We also note that forecasted errors are more correlated when pairs of firms are more

similar in terms of size and book-market ratios as indicated by the negative coefficients on these variables. This is consistent with greater economic comparability resulting in more systematic forecast errors.

5.2 FIRM-LEVEL COMPARABILITY

In the previous sections we investigated the consequences of pairwise firm i - firm j level comparability. The following sections examine the benefits to analysts of aggregated firm-i level comparability.

5.2.1. Sample and Dependent Variables. To test our comparability hypotheses we restrict the sample to firms with available data to compute the dependent variables and the control variables. The sample consists of 20,928 firm-year observations with a December fiscal year end. (This is the sample for the analyst coverage tests; the sample is smaller for the remaining dependent variables.)

The four dependent variables in the tests below are defined as follows. *Coverage (Raw)* is the number of analysts issuing an annual forecast for firm i in year t. *Coverage*, the logarithm of *Coverage (Raw)*, is used in our tests.

Analyst forecast accuracy is the absolute value of the forecast error:

$$Accuracy_{it} = |Fcst\ EPS_{it} - Actual\ EPS_{it}|/Price_{it-1} \times -100. \tag{9}$$

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. As the absolute forecast error is multiplied by -100, higher values of *Accuracy* imply more accurate forecasts.

Dispersion is the cross-sectional standard deviation of individual analysts' annual forecasts for a given firm, scaled by price, multiplied by 100.

Table 5, Panel A presents descriptive statistics for the dependent variables and comparability measures. The mean (median) number of analysts covering the firm is eight (five) analysts and is in line with studies such as Barth, Kasznik, and McNichols [2001] and O'Brien, McNichols, and Hsiou-Wei [2005]. Mean forecast accuracy is 5.0% of share price, which is slightly higher than that found in Heflin, Subramanyam, and Zhang [2003], for example. The mean forecast dispersion is 0.9% of share price, which is slightly lower than in Heflin, Subramanyam, and Zhang [2003]. The mean value for *CompAcct4* is -0.6, suggesting that the average error in quarterly earnings for the top four firms with the highest accounting comparability to firm *i* is 0.6% of market value. By construction, this value is greater than the mean value for *CompAcctInd* which is -2.5.

[Table 5]

5.2.2. Analyst Coverage Tests. To test our first hypothesis, whether analyst coverage and comparability are positively related, we estimate the following firm-level OLS regression:

$$Coverage_{it+1} = \alpha + \beta_1 \, Comparability_{it} + \gamma \, Controls_{it} + \varepsilon_{it+1}. \tag{10}$$

Comparability is one of the firm-level comparability measures – *CompAcct4* or *CompAcctInd*. We control for other factors motivating an analyst to cover firm *j* as described in the prior section. We also include industry fixed effects. Throughout the remaining analysis, for continuous variables we either take the logarithm of it or winsorize the data annually at the 1% and 99% percentiles. Because the estimation of equation 10 likely suffers from cross-sectional and time-series dependence, we estimate the model as a panel and cluster the standard errors at the firm and year levels (Petersen [2009]).

Panel B of Table 5 provides the correlation matrix for the analyst coverage test variables. Consistent with our predictions, analyst coverage is positively correlated with the comparability measures (e.g., Pearson correlation of 0.12 with *CompAcct4* and 0.18 with *CompAcctInd*). The Pearson correlation between the comparability measures equals 0.88. Also of note in Panel B, larger firms and firms with higher earnings predictability have higher comparability, whereas firms with higher R&D spending and greater earnings volatility and return volatility tend to have lower levels of our comparability measure.

Table 6 presents the regression results. Both accounting comparability measures (*CompAcct4* and *CompAcctInd*) are positively associated with analyst coverage. In terms of economic significance, a one-standard-deviation change in *CompAcct4* is associated with an increase in the logarithm of analyst following of 0.10 (= 0.018 × 5.70). Given that the median firm in our sample is covered by 5 analysts, this effect translates to an increase of 0.48 (= exp (1.6 + 0.10)) analysts, a relative increase in analyst coverage of 10%, suggesting that the effect is modestly significant on an economic basis. The economic significance is similar when we use *CompInd Acct* as our comparability measure. Overall, the regression results in Table 6 confirm the conditional analyst coverage findings in Table 4, and are consistent with hypothesis 1, which predicts a positive association between analyst coverage and comparability.

[Table 6]

5.2.3. Forecast Accuracy and Dispersion Tests. To test hypothesis 2 we estimate the following OLS specification:

$$\textit{Forecast Metric}_{it+1} = \alpha + \beta_1\,\textit{Comparability}_{it} + \gamma\,\textit{Controls}_{it} + \varepsilon_{it+1}. \tag{11}$$

Forecast Metric is *Accuracy* or *Dispersion*. Hypothesis 2 predicts that accuracy is increasing in comparability, and that dispersion is decreasing in 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 the prior year. Firms with greater variability are more difficult to forecast, so forecast errors should be greater (e.g., Kross, Ro, and Schroeder [1990], 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. *Neg SI* equals the absolute value of the special item deflated by total assets if negative, zero otherwise. $Days_{it}$ 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 (Sinha, Brown and Das [1997], Clement [1999], Brown and Mohd [2003]). We also control for *Size* because firm size is related to analysts' forecast properties (e.g., Lang and Lundholm [1996]). Last, we include industry fixed effects. Similar to the estimation of equation 10, we estimate the model as a panel and cluster the standard errors at the firm and year levels.

Panel C of Table 5 presents the correlation matrix for the analyst accuracy and dispersion test variables. As expected, forecast accuracy is positively correlated with the comparability measures (e.g., Pearson correlation of 0.13 with *CompAcct4* and 0.18 with *CompAcctInd*). Similarly, dispersion is negatively associated with firm comparability (e.g., Pearson correlations of -0.16 with *CompAcct4* and -0.25 with *CompAcctInd*). In addition, the panel shows that comparability is lower for firms with more extreme earnings surprises, firms reporting losses and negative earnings surprises, and firms with negative special items.

Table 7, models 1 and 2 present the regression results for analysts' forecast accuracy. Comparability is positively associated with accuracy. In terms of economic significance, a one-standard-deviation change in *CompAcct4* is associated with an increase in accuracy of about 1.13% (=0.018 x 62.63) of stock price, which represents an improvement in accuracy of about 23% for the average firm in the sample. The economic significance of *CompAcctInd* is similar. The results for forecast dispersion are presented in models 3 and 4 of Table 7. As predicted, comparability is negatively associated with forecast dispersion. A one-standard-deviation change in *CompAcct4* results in a reduction in forecast dispersion of 27%.

[Table 7]

In sum, these results provide evidence to support our hypotheses that comparability is positively related to forecast accuracy and negatively related to forecast dispersion. These results support the idea that analysts benefit from the higher quality information sets associated with firms that have higher comparability.

5.3   ADDITIONAL ANALYSIS: ALTERNATIVE MEASURES OF COMPARABILITY

In this section we elaborate on our measure of comparability to highlight potential limitations of our empirical approach (as described in section 2 and used thus far). In constructing our measure we make a series of assumptions that could be questioned on the grounds of prior empirical research. This section discusses these issues and assesses the impact of these changes on our results.

Our methodology implicitly assumes that the rate at which economic information is incorporated into prices is the same across firm pairs. The next subsection motivates and discusses an alternative measure that alleviates this concern. The second subsection presents an alternative empirical measure that builds on a different conceptual idea of comparability based

on correlated financial statements. The last subsection presents the results of our analyst coverage, accuracy, and dispersion tests using these two alternative measures.

5.3.1. Prices lead earnings. Prior research documents that stock prices incorporate firm-specific news before they are reported in accounting earnings, that is, "price lead earnings" (e.g., Collins et al. [1994]). To the extent that the lead-lag relation between return and earnings are an artifact of the accounting process (i.e., differential timeliness of information incorporation), our *CompAcct* measure appropriately captures this difference in accounting process to classify firms in terms of accounting comparability. However, it is possible that prices lead earnings is also driven by circumstances beyond financial reporting (e.g., institutional following). Two firms with equally timely accounting earnings could be classified as non-comparable because of outside activities influencing stock return before our measurement of quarterly return.

To address this concern, we incorporate lagged price changes into our accounting model by re-estimating *CompAcct* using the following model:

$$Earnings_{it} = \alpha_i + \beta_{1i}\, Return_{it} + \beta_{2i}\, Return_{it-1} + \varepsilon_{it}. \tag{12}$$

Return$_{it-1}$ is the stock price return during the prior quarter.[10] *CompAcct-PLE* is the revised firm-year measure of comparability based on this 'prices-lead-earnings' model.[11]

5.3.2. Correlated financial statements. Our measure of comparability so far is based on the distance between accounting earnings for two firms with (by construction) identical

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[10] As an additional robustness test, we re-estimate *CompAcct* using equation (2) but instead of the quarterly return we use the return for the contemporaneous 15-month window starting 12 months before the end of the quarter and ending three months after the end of the current quarter. Untabulated results produce inferences similar to the tabulated results.

[11] We also consider the asymmetric timeliness of earnings as a possible source of bias in our measure of comparability (Basu [1997]; Ball, Kothari, and Robin [2000]) To incorporate asymmetric timeliness into our measure, we estimate the firm's asymmetric accounting response to gains and losses by adopting a firm-specific estimation of Basu's piece-wise linear model (in lieu of equation 2). Specifically, we include an indicator variable equal to one if returns are negative and an interaction term of this indicator variable and return. We then follow our previous algorithm to measure the distance between firms' accounting functions to create a revised firm-year measure of accounting comparability. Untabulated results using this measure produce inferences that are similar to those tabulated using the *CompAcct-PLE* variable.

economic events. The advantage of this approach is that it explicitly controls for the economic event in an attempt to isolate accounting comparability. However, one could argue that accounting earnings could fulfill a comparability role to investors even when the accounting functions per se are not identical. Specifically, one could imagine two firms in which accounting earnings covary over time such that information about the earnings of one firm can be informative to an investor interested in forecasting the earnings of another firm. Further, one advantage of this alternative notion of comparability is that it does not require us to specify and estimate the accounting system, which, as we discuss above, is a limitation of our primary *CompAcct* measure.

To implement this alternative measure, we first compute the pair-wise historical correlation between the earnings of two firms among all possible pairs of firms in the same industry. More specifically, using 16 quarters of earnings data we estimate:

$$Earnings_{it} = \Phi_{0ij} + \Phi_{1ij}\,Earnings_{jt} + \varepsilon_{ijt}. \tag{13}$$

We define our firm i – firm j correlation measure of comparability (*CompAcct-R^2*) as the adjusted R^2 from this regression. Higher values indicate higher comparability. Following a similar procedure to our development of the *CompAcct* variables above, we obtain a correlation measure for each firm i - firm j pair for J firms in the same 2-digit SIC industry with available data. We then compute a firm-year measure of comparability as the average R^2 for the four firms j with the highest R^2s (*CompAcct-R^2*).[12]

While *CompAcct-R^2* intentionally broadens the definition of accounting to incorporate the effect of economic events on earnings, a concern is that it could be mainly driven by differences

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[12] Another difference between this measure and our primary measure *CompAcct* is that the latter compares *predicted* earnings while the former compares *actual* earnings. This is important because for many firms the ability of returns to explain earnings is limited. For example, two firms could have the same accounting function but one firm could have significantly more volatile earnings. This would show up as differences in the function's error term, which the *CompAcct* measure ignores but which would be reflected in *CompAcct-R^2*.

in the economic events, as opposed to in the accounting of these events. We attempt to control for this confounding factor by controlling for return and cash flow correlations across firms measured analogously to *CompAcct-R²*. Specifically, *CompCFO-R²* is created in an identical manner to *CompAcct-R²* except that in equation 13 we replace *Earnings* with *CFO*, which is the ratio of quarterly cash flow from operations to the beginning of period market value. *CompRet-R²* is also defined in a manner that parallels the construction of *CompAcct-R²*, with the exception that we use monthly stock returns (instead of earnings) taken from the CRSP Monthly Stock file, and instead of 16 quarters we use 48 months. The idea is that *CompCFO-R²* captures covariation in near-term economic shocks while *CompRet-R²* captures covariation in economic shocks related to cash flow expectations over long horizons.

5.3.3. Results. Table 8 presents the results of using the two alternative measures of comparability. Panel A replicates the Table 6 analyst coverage tests. When using *CompAcct-PLE* (column 1), the coefficient on comparability is positive and statistically significant. In column 2 the coefficient for the measure based on correlated earnings (*CompAcct-R²*) is also positive and statistically significant, as expected. We note that this regression includes two additional variables to better control for the economics: *CompCFO-R²* and *CompRet-R²*. The coefficient on the former is not significant while the coefficient on the latter is positive and statistically significant. Coefficients on the remaining control variables across all columns load with similar signs and at similar levels of statistical significance to those in Table 6.

[Table 8]

Panel B of Table 8 replicates Table 7's accuracy and dispersion tests using the alternative measures. The coefficient on *CompAcct-PLE* is positive and statistically significant for the accuracy test in column 1, and negative and statistically significant for the dispersion test in

column 3. In the case of *CompAcct-R^2*, the coefficient on this variable is not significant in either test. This suggests that while the covariation in earnings helps attract analysts to follow the firm, it doesn't necessarily improve their forecast ability.

Overall, these two alternative measures provide corroborating evidence that financial statement comparability is positively associated with analyst coverage. In addition, for the first measure the results in Table 8 corroborate that financial statement comparability is positively associated with analyst forecast accuracy and reduced analyst dispersion.

5.4   FURTHER ROBUSTNESS TESTS

In this section we discuss the untabulated results of several additional tests. The primary motivation of these additional tests is the need to better control for the economics of the events. Without perfect controls for the economics, we admit the possibility that the economics could drive both the nature of the reporting and aspects of the analysts' behavior. The following describes each test. Results for each of these tests are similar to the tabulated tests.

a) The tabulated analysis is based on a definition of industry at the two-digit SIC code level, which is imperfect (see, e.g., Bhojraj, Lee, and Oler [2003]). We also re-estimate our measures and tests using the more-fine four-digit SIC industry and an alternative Fama-French [1997] (48 industry groups) definitions of industry.

b) We re-estimate our primary tests in Tables 3, 4, 6, and 7 but include *CompCFO-R^2* and *CompRet-R^2* in each specification to better control for differences in economic events over the estimation period.

c) We re-estimate our tests in Tables 6 and 7 where we split our sample firms into two equally sized groups based on whether their market value is larger or smaller than that of the median firm in our sample. The motivation for this analysis parallels the motivation for our

analyses in Tables 3 and 4 in which we directly matched the treatment firms with benchmark firms of similar size and book-market. These results for size and book-market partitions also address another issue with our tests. Throughout the analysis we implicitly assume an efficient market: Quarterly returns reflect changes in firm value, not shifts in investor expectations about payoffs and/or risk that are uncorrelated with the firm's true fundamental performance and economic condition (i.e., returns reflect changes in investor sentiment, behavioral biases, unraveling of investor optimism/pessimism, etc.). But studies such as Lakonishok, Shleifer, and Vishny [1994] and Dechow and Sloan [1997] provide evidence linking the poor returns of growth stocks to over-optimism in future earnings performance and growth. In these partitioned-sample tests we compare firms with other firms that likely have similar exposure to market pricing inefficiencies (e.g., small versus small firms; high-growth versus high-growth firms within an industry).

The results for these smaller samples are generally robust. Specifically, the result with analyst coverage is weaker for smaller firms. On the other hand, the result with forecast accuracy is weaker for larger firms. We also partition our sample into higher and lower book-market firms. These results hold for each group with no qualification.

6. Conclusions

This paper develops a measure of financial statement comparability and then studies the effect of this measure on analysts. A key innovation is the development of an empirical, firm-specific, output-based, quantitative measure of financial statement comparability. It is based on the idea that for a given set of economic events, firms with comparable accounting systems will produce similar financial statements. We first provide construct validity for our measure. The likelihood of an analyst using firm j as a benchmark when analyzing firm i in a report is

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increasing in the comparability between firms i and j. This suggests that our measure is correlated with the use of comparable firms in analysts' reports.

We then test whether comparability manifests any benefits to financial statement users as gleaned from the effect on analyst coverage and the properties of their forecasts. Analyst coverage is increasing in comparability. Tests also indicate that the likelihood that an analyst covering firm i is also covering firm j is increasing in the comparability betweens firms i and j. Hence, we not only show that comparability leads to greater analyst following, but also specifically predict which other firms an analyst will follow. In addition, the results suggest that comparability is positively associated with forecast accuracy and negatively associated with forecast dispersion. These results provide evidence consistent with our hypotheses that comparability lowers the cost of acquiring information, and increases the overall quantity and quality of information available to analysts about the firm.

We believe our financial statement comparability measure could be used to help assess changes in comparability as a result of changes in accounting measurement rules or reporting standards, accounting choice differences, or of adjustments. For example, 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" (our emphasis) (IASCF [2005]). Our measure could be used to assess whether IFRS achieves its intended consequence of enhanced financial statement comparability (see e.g., Barth et al. [2009], Beuselinck, Joos, and Van Der Meulen [2007]).

Notwithstanding the above benefits, some caveats are in order. We do not study the determinants of financial statement comparability and thus we cannot speak to a firm's

equilibrium level of comparability. Our results are consistent with higher financial statement comparability enriching firms' information environments, and thus providing tangible benefits for firms. We do not, however, study comparability's other potential benefits and costs to firms. Our analysis is also silent on what firms could do to improve cross-sectional comparability. Furthermore, while earnings are arguably the most important summary measure of accounting performance, a limitation is that earnings captures only one financial statement dimension, specifically an income statement perspective. For example, balance sheet numbers are of prime interest to lenders, credit rating agencies, bank regulators, etc. An opportunity exists to create a multi-dimensional financial statement measure of comparability.

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APPENDIX
Variable Definitions

Variable	Definition
Accrual Quality	= Measure of accruals quality developed by Dechow and Dichev [2002] and used by Francis et al. [2005].
Accuracy	= Absolute value of the forecast error multiplied by -100, 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.
AnalystComp	= 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.
Book-Market	= Ratio of the book value to the market value of equity.
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.
CorrFcstError	= Absolute value of the difference between scaled analyst forecast errors for firms i and j, multiplied by -1, where scaled forecast error is I/B/E/S analysts' mean annual earnings forecast less the actual earnings as reported by I/B/E/S, scaled by the stock price at the end of the prior fiscal year calculated separately for firms i and j.
Coverage	= Logarithm of the number of analysts issuing a forecast for the firm.
Coverage (Raw)	= Number of analysts issuing a forecast for the firm.
CompAcct	= The absolute value of the difference of the predicted value of a regression of firm i's earnings on firm i's return using the estimated coefficients for firms i and j respectively. 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.
CompAcct4	= Average of the four highest *CompAcct* values for firm i.
CompAcctInd	= Median *CompAcct* for firm i for all firms in firm i's industry.
CompAcct-PLE	= A firm-level alternative measure of *CompAcct4* used in sensitivity tests that is adjusted for systematic differences in the ability of prices to lead earnings across firms.
CompAcct-R^2	= A firm-level alternative measure of *CompAcct4* used in sensitivity tests. The R^2 from a regression of firm i's quarterly earnings on the quarterly earnings of firm j 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. A firm-level measure is calculated by taking the average of the four highest firm i – firm j measures.
CompCFO-R^2	= Calculated in a similar way to *CompAcct-R^2* but using cash flow from operations instead of earnings.
CompRet-R^2	= Calculated in a similar way to *CompAcct-R^2* but using returns instead of earnings.
Days	= Logarithm of the number of days from the forecast date to the earnings announcement date.
Depreciation	= Firm's depreciation expense scaled by total sales, less the respective 2-digit SIC industry mean value of depreciation expense scaled by total sales.
Dispersion	= Cross-sectional standard deviation of individual analysts' annual forecasts, scaled by the stock price at the end of the prior fiscal year.
Issue	= Indicator variable that equals one if the firm issues debt or equity securities during the preceding, current or following year, zero otherwise.
Loss	= Indicator variable that equals one if the current earnings less than zero, zero otherwise.

(*Continued*)

Variable	Definition
Neg SI	= Absolute value of the special item deflated by total assets if negative, zero otherwise.
Neg UE	= Indicator variable that equals one if firm i's earnings are below the reported earnings a year ago, zero otherwise.
Predictability	= R^2 of a regression of annual earnings on prior-year annual earnings for the same firm.
R&D	= Firm's research and development expense scaled by total sales, less the respective 2-digit SIC industry mean value of research and development expense scaled by total sales.
Size	= Logarithm of the market value of equity measured at the end of the year.
Size-$	= Market value of equity measured at the end of the year.
Smoothness	= Ratio of the standard deviation of earnings to the standard deviation of cash flows (Leuz, Nanda and Wysocki [2003], Francis et al., [2004])
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.
Volatility Earn	= Standard deviation of 16 quarterly earnings.
Volatility Ret	= Standard deviation of 48 months of stock returns.
Volume	= Logarithm of trading volume in millions of shares during the year.

Suffix

Difference	= Absolute value of the difference between firm i's and firm j's respective variables.

TABLE 1

Descriptive Statistics from Estimation of Equation 2

Variable	No. of Obs	Mean	STD	10th Percent	Median	90th Percent
Intercept (α_i)	71,295	0.00	0.04	-0.04	0.01	0.03
β_i coefficient	71,295	0.02	0.08	-0.03	0.01	0.08
Regression R^2 (%)	71,295	12.18	13.94	0.26	6.93	32.17

This table provides descriptive statistics of the intercept, beta coefficient, and the R^2 from firm-year specific regressions:

$$Earnings_{it} = \alpha_i + \beta_i\, Return_{it} + \varepsilon_{it}.$$

where *Earnings* is the ratio of quarterly net income before extraordinary items to the beginning-of-period market value of equity, and *Return* is the stock price return during the quarter. Each regression is estimated for each firm-year using the 16 previous quarters of data.

TABLE 2

Financial Statement Comparability Descriptive Statistics for a
Random Sample of Firm i – Firm j Pair Observations

Panel A: No Partitions		$CompAcct_{ijt}$ (all numbers in %)				
	No. of Obs.	Mean	STD	10th Percent	Median	90th Percent
Full Sample	635,777	-5.1	7.2	-0.5	-2.7	-11.5

Panel B: Economic partitions		$CompAcct_{ijt}$ (all numbers in %)	
	No. of Obs.	Mean	Median
By Industry			
Firms *i* and *j* in banking industry	227	-2.7	-1.2
Firm *i* in banking while firm *j* in manufacturing industry	6,453	-4.2	-2.0
Firm *i* in banking while firm *j* in utility industry	1,128	-4.1	-1.4
By *Size*			
Firm *i* in same extreme quintile as firm *j*	50,593	-5.6	-2.5
Firm *i* in opposite extreme quintile than firm *j*	51,089	-6.7	-3.6
By *Book-Market*			
Firm *i* in same extreme quintile as firm *j*	50,452	-6.0	-3.6
Firm *i* in opposite extreme quintile than firm *j*	51,063	-6.1	-3.7

Panel C: Earnings Attributes partitions		$CompAcct_{ijt}$ (all numbers in %)	
	No. of Obs.	Mean	Median
By *Accrual Quality*			
Firm *i* in same extreme quintile as firm *j*	50,383	-5.3	-2.8
Firm *i* in opposite extreme quintile than firm *j*	51,195	-6.1	-3.7
By *Predictability*			
Firm *i* in same extreme quintile as firm *j*	50,578	-4.8	-2.4
Firm *i* in opposite extreme quintile than firm *j*	50,656	-5.1	-2.7
By *Smoothness*			
Firm *i* in same extreme quintile as firm *j*	50,441	-4.4	-2.0
Firm *i* in opposite extreme quintile than firm *j*	51,102	-5.3	-3.0
By *Loss*			
Firms *i* and *j* both report losses or both report profits	375,929	-3.7	-1.6
Firm *i* reports a loss but firm *j* reports a profit or vice versa	259,848	-7.1	-5.0

This table provides descriptive statistics for our *CompAcct* measure. We randomly select a sample of 10% of the available firm *i* – firm *j* pairs in the year 2005. Panel A presents descriptive statistics for *CompAcct* for the full random sample of firm *i* – firm *j* observations. Panel B partitions the sample by economic characteristics—industry, size, and book-market. Panel C partitions the sample by earnings attributes—accrual quality, predictability, smoothness, and whether the firm reports a loss. In the case of size, book-market, accrual quality, predictability, and smoothness partitions, we compare firm-pair observations in which the firms *i* and *j* are in the most extreme quintiles of the respective factor. For each partition type, all differences between mean *CompAcct* for each group are significantly different (at the 1% two-sided level), with the following exception. In the Industry partition, the mean *CompAcct* Firm *i* in banking while firm *j* in manufacturing industry group is not significantly different than the mean *CompAcct* Firm *i* in banking while firm *j* in utility industry group. Variables are defined in the appendix.

TABLE 3

Use of Comparable Firms in Analysts' Reports

	Prediction	Match on Industry (1)	Match on Industry, Size, and Book-Market (2)
CompAcct$_{ij}$	+	**0.05*** **	**0.03*** **
		(5.92)	**(2.76)**
Size$_j$	+	0.06***	-0.03
		(3.41)	(-1.43)
Book-Market$_j$	?	-0.01	0.01
		(-0.81)	(0.69)
Volume$_j$	+	0.16***	0.09***
		(10.06)	(4.50)
ROA$_j$	?	0.01	-0.01
		(0.90)	(-0.95)
Predictability$_j$	+	0.01	0.01
		(1.30)	(0.77)
Volatility Earn$_j$	–	0.00	0.01
		(0.13)	(0.30)
Volatility Ret$_j$	–	-0.02**	-0.01
		(-1.80)	(-0.39)
Size Difference$_{ij}$	–	-0.12***	
		(-11.43)	
Book-Market Difference$_{ij}$	–	-0.00	
		(-0.68)	
Pseudo R^2		10.91%	4.82%
No. of Obs.		9,894	9,894

This table reports an analysis of the relation between the pairwise financial statement comparability measures (i.e., at the firm i – firm j level) and analysts' use in their reports of firms j in the same industry as the sample firm i for the year 2005. We estimate various specifications of the following pooled Probit model:

$$AnalystComp_{ikj} = \alpha + \beta_1 \, CompAcct_{ij} + \gamma \, Controls_j + \varepsilon_{ikj}.$$

The dependent variable equals one if firm j is chosen as a peer by the analyst for firm i. In Column 1, the benchmark firm-j peers not chosen by analysts are randomly selected from a pool of companies with available data in the same 2-digit SIC. In Column 2, the benchmark firm-j peers not chosen by analysts are selected from a pool of companies with available data in the same 2-digit SIC and that have the closest distance in size and book-market to firm i. Industry fixed effects are included but not tabulated. The reported coefficient is the elasticity, which represents the change in the probability of a peer being selected for a one-standard-deviation change in the independent variable. Coefficient z-statistics are in parentheses and are clustered at the firm and analyst level. ***, **, and * denote significance at the 1%, 5%, and 10% (two-sided) levels, respectively. Variables are defined in the appendix.

TABLE 4
Correlated Analysts' Coverage and Forecast Errors of Comparable Firms

		Correlated Analyst Coverage		Correlated Analyst Forecast Errors	
			Match on Industry, Size, and		
		Match on Industry	Book-Market		
	Prediction	(1)	(2)	Prediction	(3)
$CompAcct_{ijt}$	+	**0.03*****	**0.03*****	+	**0.34*****
		(7.46)	**(8.55)**		**(5.44)**
$Size_{jt}$	+	0.13***	-0.07***	+	0.42***
		(18.94)	(-13.61)		(16.53)
$Book\text{-}Market_{jt}$	?	0.00	-0.01***	?	-0.00
		(1.46)	(-6.78)		(-0.24)
$Volume_{jt}$	+	0.15***	0.12***	?	-0.24***
		(24.16)	(20.47)		(-11.17)
ROA_{jt}	?	-0.02***	-0.01***	?	0.14***
		(-5.25)	(-4.43)		(11.77)
$Predictability_{jt}$	+	0.01***	0.01***	+	0.01**
		(4.27)	(3.97)		(2.05)
$Volatility\ Earn_{jt}$	–	-0.01**	0.00*	–	0.02*
		(-2.49)	(1.67)		(1.84)
$Volatility\ Ret_{jt}$	–	-0.03***	-0.02**	–	0.03*
		(-4.36)	(-2.39)		(1.70)
$Size\ Difference_{ijt}$	–	-0.10***		–	-0.11***
		(-22.57)			(-7.92)
$Book\text{-}Market\ Difference_{ijt}$	–	-0.01***		–	-0.05**
		(-4.39)			(-2.56)
Pseudo R^2		20.51%	1.32%		16.3%
No. of Obs.		2,147,780	2, 147,780		952,182

This table reports an analysis of the relation between the pairwise financial statement comparability measures (i.e., at the firm i – firm j level) and both analyst coverage and forecast errors of firms j in the same industry as the sample firm i. In columns 1 and 2 we estimate various specifications of the following pooled Probit model:

$$CondCoverage_{ikjt} = \alpha + \beta_1\ CompAcct_{ijt} + \gamma\ Controls_{jt} + \varepsilon_{ikjt}.$$

The dependent variable equals one if the firm j is covered by the analyst who covers firm i. In column 1, the benchmark firm-j peers not covered by analysts are randomly selected from a pool of companies with available data in the same 2-digit SIC. In column 2, the benchmark firm-j peers not covered by analysts are selected from a pool of companies with available data in the same 2-digit SIC and that have the closest distance in size and book-market to firm i. Industry fixed effects are included but not tabulated. The reported coefficient is the elasticity, which represents the change in the probability of a peer being selected for a one-standard-deviation change in the independent variable. In Column 3 we estimate the same model as in Column 1 but use *CorrFcstError* as the dependent variable, which proxies for the correlation in forecast errors between firms i and j. The sample consists of pairs of firms i-j observations in which analysts cover both firms. Coefficient z- and t-statistics are in parentheses and are clustered at the firm and analyst level. ***, **, and * denote significance at the 1%, 5%, and 10% (two-sided) levels, respectively. Variables are defined in the appendix.

TABLE 5

Descriptive Statistics and Correlations for Variables at the Firm-i Level

Panel A: Descriptive statistics for dependent variables and comparability (all numbers are in %)

Variable	No. of Obs	Mean	STD	10th Percent	Median	90th Percent
Coverage (Raw)	20,928	7.6	7.2	1	5	18
Coverage	20,928	1.6	1.0	0.0	1.6	2.9
Accuracy	19,187	-5.0	15.3	-9.9	-1.1	-0.1
Dispersion	14,544	0.9	2.5	0.1	0.3	1.9
CompAcct4	20,928	-0.6	1.8	-1.2	-0.2	0.0
CompAcctInd	20,928	-2.5	3.6	-4.8	-1.5	-0.6

Panel B: Correlations between variables in analyst coverage (Table 6) tests

		(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)
Coverage	(I)	0.123*	0.175*	0.727*	-0.210*	0.654*	-0.068*	0.086*	0.063*	0.039*	-0.221*	-0.252*
CompAcct4	(II)		0.884*	0.027*	-0.022*	-0.014*	-0.007	-0.051*	-0.021*	0.045*	-0.158*	-0.190*
CompAcctInd	(III)			0.122*	0.046*	-0.053*	-0.159*	-0.051*	-0.018*	0.087*	-0.375*	-0.407*
Size	(IV)				-0.317*	0.712*	-0.146*	0.029*	0.061*	0.053*	-0.317*	-0.429*
Book-Market	(V)					-0.261*	-0.172*	0.052*	-0.140*	-0.017*	-0.185*	-0.063*
Volume	(VI)						0.102*	0.052*	0.076*	-0.056*	0.063*	0.081*
R&D	(VII)							0.018*	0.007	-0.105*	0.468*	0.401*
Depreciation	(VIII)								0.030*	-0.052*	-0.016*	0.030*
Issue	(IX)									-0.040*	0.029*	0.048*
Predictability	(X)										-0.097*	-0.167*
Volatility Earn	(XI)											0.625*
Volatility Ret	(XII)											

(Continued)

TABLE 5 – *Continued*

Panel C: Correlations between variables in analysts' forecast accuracy and dispersion (Table 7) tests

		(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)	(XIII)
Accuracy	(I)	-0.601*	0.130*	0.183*	-0.075*	-0.125*	-0.269*	-0.087*	-0.002	0.240*	0.047*	-0.196*	-0.216*
Dispersion	(II)		-0.160*	-0.253*	0.123*	0.151*	0.344*	0.119*	0.013	-0.238*	-0.061*	0.286*	0.271*
CompAcct4	(III)			0.884*	-0.270*	-0.001	-0.130*	-0.078*	0.030*	-0.002	0.048*	-0.146*	-0.174*
CompAcctInd	(IV)				-0.304*	-0.026*	-0.298*	-0.147*	0.035*	0.086*	0.089*	-0.359*	-0.390*
SUE	(V)					-0.010	0.130*	0.158*	0.019*	0.246*	-0.071*	0.095*	0.106*
Neg UE	(VI)						0.347*	0.176*	-0.017*	-0.119*	-0.064*	0.097*	0.090*
Loss	(VII)							0.278*	-0.041*	-0.310*	-0.119*	0.471*	0.478*
Neg SI	(VIII)								-0.008	-0.071*	-0.037*	0.230*	0.167*
Days	(IX)									0.128*	0.020*	-0.064*	-0.056*
Size	(X)										0.051*	-0.289*	-0.409*
Predictability	(XI)											-0.099*	-0.172*
Volatility Earn	(XII)												0.617
Volatility Ret	(XIII)												

This table reports descriptive statistics and correlations for the variables used in the Tables 6 and 7 tests. The sample is restricted to observations at the firm-*i* level with available data to calculate all the variables in this analysis. Panel A presents descriptive statistics for the dependent and comparability measure variables. Panel B presents Pearson correlations between the Table 6 test variables. Panel C presents Pearson correlations between the Table 7 test variables. Variables are defined in the appendix. * denotes significance at the 10% (two-sided) level.

TABLE 6

Financial Statement Comparability and Analyst Coverage

	Prediction	(1)	(2)
CompAcct4$_{it}$	+	**5.70*****	
		(9.37)	
CompAcctInd$_{it}$	+		**3.18*****
			(7.67)
Size$_{it}$	+	0.24***	0.24***
		(16.15)	(15.96)
Book-Market$_{it}$	–	0.06*	0.05*
		(1.93)	(1.77)
Volume$_{it}$	+	0.21***	0.22***
		(13.05)	(13.02)
R&D$_{it}$	+	0.20***	0.20***
		(2.60)	(2.60)
Depreciation$_{it}$	+	0.33	0.37*
		(1.63)	(1.89)
Issue$_{it}$	+	0.04	0.03
		(1.64)	(1.50)
Predictability$_{it}$	+	0.05	0.05
		(1.23)	(1.23)
Volatility Earn$_{it}$	–	-2.18***	-1.74***
		(-6.00)	(-4.77)
Volatility Ret$_{it}$	–	-1.05***	-0.90***
		(-3.96)	(-3.19)
Adj. R^2		62.21%	62.24%
No. of Obs.		20,928	20,928

This table reports an analysis of the relation between financial statement comparability and analyst coverage. The sample is restricted to observations at the firm-*i* level with available data to calculate all the variables in this analysis. The table reports the results of various specifications of the following OLS regression:

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

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 and year level. Coefficient *t*-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% (two-sided) levels, respectively. Variables are defined in the appendix.

TABLE 7

Financial Statement Comparability and Analysts' Forecast Accuracy and Dispersion

		Dep. Var. = *Accuracy*			Dep. Var. = *Dispersion*	
	Pred.	(1)	(2)	Pred.	(3)	(4)
CompAcct4$_{it}$	+	**62.63*****		–	**-13.34*****	
		(2.69)			**(-2.81)**	
CompAcctInd$_{it}$	+		**36.64*****	–		**-9.53*****
			(3.12)			**(-3.33)**
SUE$_{it}$	–	-0.08***	-0.08**	?	0.02***	0.02***
		(-2.71)	(-2.54)		(3.18)	(2.97)
Neg UE$_{it}$	–	-1.44***	-1.50***	+	0.23***	0.25***
		(-5.28)	(-5.56)		(4.17)	(4.54)
Loss$_{it}$	–	-5.38***	-5.23***	+	1.13***	1.09***
		(-7.18)	(-7.00)		(7.80)	(7.72)
Neg SI$_{it}$	–	0.28	0.47	+	0.06	-0.01
		(0.11)	(0.19)		(0.05)	(-0.01)
Days$_{it}$	–	-1.90***	-1.88***	+	0.20**	0.19**
		(-5.77)	(-5.80)		(2.34)	(2.26)
Size$_{it}$	+	1.62***	1.62***	–	-0.28***	-0.28***
		(7.89)	(7.91)		(-10.59)	(-10.59)
Predictability$_{it}$	+	-0.41	-0.40	–	0.05	0.05
		(-0.92)	(-0.91)		(0.55)	(0.57)
Volatility Earn$_{it}$	–	-28.02**	-23.64*	+	12.25**	11.02**
		(-2.12)	(-1.75)		(2.23)	(2.01)
Volatility Ret$_{it}$	–	-7.49	-5.91	+	1.73	1.20
		(-0.96)	(-0.77)		(1.61)	(1.13)
Adj. R^2		11.49%	11.54%		16.77%	17.20%
No. of Obs.		19,187	19,187		14,544	14,544

This table reports an analysis of the relation between financial statement comparability and analyst forecast accuracy and dispersion. The sample is restricted to observations at the firm-*i* level with available data to calculate all the variables in this analysis. The table reports the results of various specifications of the following OLS regression:

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

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 and year level. Coefficient *t*-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% (two-sided) levels, respectively. Variables are defined in the appendix.

TABLE 8
Alternative Measures of Comparability

Panel A: Financial statement comparability and analyst coverage

	Prediction	*CompAcct-PLE* (1)	*CompAcct-R^2* (2)
		Comparability =	
Comparability$_{it}$	+	**6.46*** ** **(9.54)**	**0.35*** ** **(4.63)**
CompCFO-R^2_{it}	+		0.02 (0.29)
CompRet-R^2_{it}	+		0.51*** (3.44)
Size$_{it}$	+	0.24*** (15.71)	0.21*** (14.96)
Book-Market$_{it}$	−	0.06** (2.00)	0.02 (0.60)
Volume$_{it}$	+	0.21*** (11.91)	0.22*** (14.38)
R&D$_{it}$	+	0.25*** (3.03)	0.26*** (2.79)
Depreciation$_{it}$	+	0.36* (1.75)	0.18 (0.78)
Issue$_{it}$	+	0.04 (1.53)	0.06*** (2.91)
Predictability$_{it}$	+	0.05 (1.27)	-0.02 (-0.46)
Earn Volatility$_{it}$	−	-1.95*** (-5.40)	-3.36*** (-7.77)
Ret Volatility$_{it}$	−	-1.04*** (-3.70)	-1.68*** (-7.08)
Adj. R^2		62.27%	61.15%
No. of Obs.		20,376	15,455

(Continued)

TABLE 8 – *Continued*

Panel B: Financial statement comparability and analysts' forecast accuracy and dispersion

	Pred.	Dep. Var. = *Accuracy* Comparability =		Pred.	Dep. Var. = *Dispersion* Comparability =	
		CompAcct-PLE (1)	*CompAcct-R^2* (2)		*CompAcct-PLE* (3)	*CompAcct-R^2* (4)
Comparability$_{it}$	+	**46.15**** **(2.51)**	**1.19** **(1.01)**	–	**-8.43***** **(-3.04)**	**-0.04** **(-0.19)**
CompCFO-R^2_{it}	+		-0.32 (-0.18)	–		0.48 (1.59)
CompRet-R^2_{it}	+		0.69 (0.41)	–		0.46** (1.99)
SUE$_{it}$	–	-0.06** (-2.34)	-0.11*** (-3.15)	?	0.01*** (3.15)	0.02*** (3.33)
Neg UE$_{it}$	–	-1.35*** (-4.28)	-1.21*** (-5.21)	+	0.21*** (3.87)	0.23*** (3.46)
Loss$_{it}$	–	-4.81*** (-7.27)	-5.26*** (-7.10)	+	1.05*** (8.22)	1.07*** (7.56)
Neg SI$_{it}$	–	-0.46 (-0.16)	1.70 (0.42)	+	0.37 (0.25)	0.17 (0.09)
Days$_{it}$	–	-1.61*** (-5.67)	-1.76*** (-5.76)	+	0.17** (2.05)	0.20 (1.55)
Size$_{it}$	+	1.44*** (8.34)	1.64*** (9.19)	–	-0.25*** (-11.54)	-0.33*** (-9.79)
Predictability$_{it}$	+	-0.30 (-0.70)	-1.16** (-1.99)	–	0.02 (0.19)	0.11 (0.90)
Earn Volatility$_{it}$	–	-32.88** (-2.48)	-37.49** (-2.15)	+	14.29** (2.34)	14.28** (2.32)
Ret Volatility$_{it}$	–	-7.93 (-1.04)	-9.72 (-1.23)	+	1.14 (0.97)	1.57 (1.44)
Adj. R^2		10.47%	11.25%		15.61%	16.20%
No. of Obs.		18,747	14,152		14,293	10,568

(Continued)

TABLE 8 – *Continued*

This table reports an analysis of the replication of the Tables 6 and 7 tests in which we use two alternative measures of comparability. Panel A replicates the Table 6 analyst coverage tests. Panel B replicates the Table 7 accuracy and dispersion tests. 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 and year level. Coefficient *t*-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% (two-sided) levels, respectively. Variables are defined in the appendix.