REPORTED EARNINGS AND ANALYST FORECASTS AS COMPETING SOURCES OF INFORMATION: A NEW APPROACH


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Abstract

Current empirical research suggests that analysts earnings forecasts provide a critical benchmark for assessing the reported earnings of a firm. Prior reported earnings also provide a potentially important input into the analyst forecasting process. Based on a large time series of analyst earnings forecasts and reported earnings, we examine their information content by using suitably adapted Granger causality tests. We test both short-term and long-term causality. We find evidence of bi-directional “causality” between analyst earnings forecasts and reported earnings. This suggests that forecasts make a significant contribution to the information set that is useful for predicting earnings, as one might expect. However, it also suggests that past earnings are incorporated in later forecasts, implying that earnings reports have positive value and that forecasts do not fully substitute for earnings reports.
1. Introduction

Over an extended period of time, a typical firm reports its quarterly earnings; then analysts forecast the next quarter’s earnings; then the firm reports earnings for that quarter; followed by further analyst forecasts … – and so the ‘earnings/forecasts’ cycle continues. Our central research question asks: what is the role played by financial analysts in informing the market of the performance of a firm via earnings forecasts and how do earnings forecasts interact with firms’ reported earnings?

Although this question is not new, the accumulated evidence supporting the conclusion that analysts provide a valuable service to investors, typically centres on the market price reactions to analyst forecasts as compared to company earnings announcements (see Frankel, Kothari and Weber, 2006; Lennox and Park, 2006; Asquith, Mikhail and Au, 2005; Gleason and Lee, 2003; Bartov et al., 2002; Skinner and Sloan, 2002; Lopez and Rees, 2001; Francis and Soffer, 1997; Lang and Lundholm, 1996). However, the pooled cross-sectional approach and use of market reactions to support the information value of various competing sources of information (viz. analyst and company earnings announcements) is dependent on a range of methodological choices – for example, the length of the event window used and the fact that tests jointly examine market efficiency and the model used. The interpretation of these results is open to debate and interpretation.1

1Notably, the empirically documented post-earnings announcement drift evidence has been used to cast doubt on the efficiency with which the market responds to earnings news. These papers include Bartov, Radhakrishnan and Krinsky (2000), Ball and Bartov (1996), Bhushan (1994) and Bernard and Thomas (1989, 1990). Also, in recent times, a price drift similar to that observed for earnings announcements has been documented for analyst forecast revision announcements. Examples of these papers include Gleason and Lee (2003), Elgars, Lo and Pfieffer (2001) and Brennan, Jegadeesh and Swaminathan (1993). There is some debate about the reasons for and interpretation of this anomaly. Our purpose in highlighting this area is to show that the issue of how earnings related information is disseminated and the market’s response to it, is still not fully resolved.
Our study seeks to establish whether the information contained in analyst forecasts are leading, contemporaneous or lagging a company’s public earnings announcement (‘reported’ earnings) through the use of a non-standard Granger causality econometric procedure. This time series approach represents a class of alternative, newer and more dynamic econometric techniques than those which have been previously applied in the capital markets literature. Notably, it does not rely on the market price reaction to information and news releases to assess the information content of these announcements.

A large body of literature has established the value relevance of earnings forecasts (see Frankel, Kothari and Weber, 2006; Asquith, Mikhail and Au, 2005; Gleason and Lee, 2003; Francis and Soffer, 1997; Lang and Lundholm, 1996). For example, Bartov et al., (2002) and Lopez and Rees (2001) have shown that the prices of securities are affected by analysts’ forecasts. That is, firms with positive forecast errors (firms’ actual earnings are greater than analysts’ forecasts), on average, tend to experience positive share price adjustments and vice versa.

In addition, there has been empirical evidence to suggest that the interaction between analysts and reported company earnings is more dynamic and complex. Lennox and Park (2006), Hutton (2005), Richardson, Teoh and Wysocki (2004) and Matsumoto (2002) provide evidence on the “earnings guidance” to analysts by management. Specifically, management guide the analysts to certain earnings levels that avoid negative earnings surprises and this suggests that while analysts’ revision announcements may pre-

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2 A standard Granger causality methodology cannot be used because the analysts’ forecasts are irregularly spaced and the actual earnings announcements are not always precisely one quarter apart in calendar time. In addition, there are many analyst forecasts for each earnings announcement.

3 Lennox and Park (2006) examine the relationship between a firm’s earnings response coefficient and the management’s issuance of earnings forecasts and document a significant positive relationship. Hutton (2005) examine the characteristics of firms that were more likely to provide guidance to analysts. Richardson, Teoh and Wysocki (2004) specifically examine the role of managerial incentives to sell stock and to guide analysts.
empt “public” earnings announcements, it does not necessarily mean that the analyst information is a substitute for earnings information. Recent studies on voluntary management earnings forecasts further confuse our understanding of the relevance and information content of different information sources (see Lennox and Park, 2006; Brown and Higgins, 2005; Skinner, 1994 and Pownall Wasley, and Waymire, 1993).

In the US, there is an emerging body of evidence which suggests that the earnings reporting process has lost some of its relevance to investors due to the availability of competing information sources (see, for example, Francis, Schipper and Vincent, 2002; Lev and Zarowin, 1999; Collins, Maydew and Weiss, 1997). Notably, analysts are able to usefully draw upon non-financial information, taking advantage of the fact that such sources are not constrained by generally accepted accounting principles (GAAP) and generally have greater timeliness when compared to earnings and financial reports.4

Another branch of the empirical literature suggests asymmetric share price reactions to falling short of and beating analysts consensus forecasts (Sequeira, Ho and Tang, 2006, Skinner and Sloan, 2002 and Lopez and Rees, 2001). Inevitably, the overwhelming evidence suggests that analysts’ forecasts have significant information content, with wealth implications for management and investors.

All of this empirical evidence suggests that the information environment for firms is dynamic and that there is a complex mutual inter-dependence between earnings forecasts and reported earnings. We develop and use an innovative time series approach on each announcing firm’s analyst forecast and actual earnings to analyse and follow in an ordered time dimension for each firm, whether analysts’ forecasts are a timely and

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4 For example, Hall, Jaffe and Trajtenberg (2005) and Deng, Lev and Narin (1999), use patents citations in their studies on predicting stock performance and market valuation, respectively.
accurate source of competing information in relation to reported earnings. In other words, the fundamental question that we address is: are analysts’ earnings forecasts substitutes, complements or simply a repeat of reported earnings?

Addressing this question is important since a clear understanding of this process is useful at two levels. First, it has implications for regulators who formulate disclosure policy. A better understanding of the process of information dissemination in markets would help regulators to frame and strengthen disclosure policy for the various market participants. Such knowledge will help regulators to frame policy that govern the practices of and relationship between analysts vis-à-vis the firms for which they provide the forecasts.\(^5\) Second, understanding the earnings/forecast linkage enhances investors’ ability to assess the value-add of information intermediaries such as analysts to the investment decision making process. In particular, the findings in our study provide important insights into whether analysts’ forecasts are a credible and timely source of earnings information using a new and rigorous time series econometric technique.

The results of our study show evidence of bi-directional “causality” i.e. that analyst earnings forecasts Granger-cause reported earnings and similarly reported earnings Granger-cause earnings forecasts. In other words, analyst earnings forecasts (reported earnings) have information content (separate from that in past earnings) that is helpful in predicting reported earnings (analyst earnings forecasts). Further, past earnings and past forecasts both provide information that is incorporated into future forecasts, This provides valuable time series evidence (in contrast to prior cross-sectionally based analysis) that affirms the mutual inter-dependence of earnings forecasts and reported earnings in a dynamic information network.

\(^5\) For example, the promulgation of the Regulation FD – Fair Disclosure by the SEC.
The remainder of the paper is structured as follows. Section 2 presents a brief literature review, while Section 3 outlines our data. In section 4, our methodology on the non-standard Granger Causality test is presented. Section 5 outlines and discusses our results and Section 6 presents our conclusion.

2. Literature Review and Hypotheses

2.1 Introduction

Alternative/competing sources of public information capable of providing insights into the direction and, to a certain extent, the magnitude of current year earnings derive from information sets that can be characterized into three broad categories: (a) company specific; (b) industry specific;\(^6\) and (c) country or economy wide.

Our direct focus in this paper will be on company specific information and analyst forecasts specific to the company. Company specific information includes prior period earnings of the company; voluntary management earnings forecasts or guidance.\(^7\) Our study is based primarily on the premise of earlier works by Ou and Penman (1989) and Beaver, Lambert and Morse (1980) which show that the permanent component of prior earnings

\(^6\) For industries that are either directly or indirectly impacted by international events, this information set can be viewed as incorporating such global information as well.

\(^7\) Foster (1981), Baginski (1987) and Clinch and Sinclair (1987) show that there are intra-industry information transfers. Companies that report earlier, provide general information about the earnings of companies in the same industry that are yet to report. Clinch and Sinclair (1987) found, that “an earnings announcement that results in a positive (negative) change in the announcing firm’s share price is generally associated with a positive (negative) change in the share prices of other firms in the same industry.” (Clinch and Sinclair, 1987, p. 90). Baginski (1987), in his examination of a firm’s management forecasts of earnings, shows that they affect the share price of non-disclosing firms in the same industry. This indicates information transfers occur across related firms. Frost (1995) using a number of different tests, produces three notable findings. First, she reaffirms the positive association between an announcing firm and other firms in the same industry. Second, the larger information content of the earnings disclosure, the larger is the information transfer. Third, econometric techniques that account for contemporaneous cross correlations produce less significant results. In our study, we do not seek to directly incorporate these effects but assume that they are information components fully captured by and incorporated into analyst forecasts.
earnings can provide explanatory power in predicting future earnings. Specifically, Ou and Penman (1989, p. 112) remark that “certain of these numbers (numbers presented in the income statement, balance sheet, and the statement of changes in financial position) can be summarized into one measure that predicts future earnings and also filters out transitory components of current earnings.” (italics added). Earnings forecasts can be viewed as a summary statistic by analysts in which they make use of information in the market, inclusive of the numbers in the financial statements of the firm, to predict the future earnings of the company. Our study capitalizes on this important premise to provide evidence on the mutual inter-dependence of the lead, lag or contemporaneous relationship between reported earnings and earnings forecasts of a firm. Our analysis provides an alternative perspective to the findings reported in previous work such as Ali, Klein and Rosenfeld (1992, p.197) which conclude that “analysts correctly use the time-series properties of annual earnings when setting their forecasts of annual EPS”.

2.2 Analysts’ role as information providers for earnings determination

Various researchers such as Francis and Schipper (1999) and Lev and Zarowin (1999) have suggested that, over time, financial accounting/earnings information seems to have generally lost relevance. An interesting and potentially quite valuable alternative source of information which can be thought of as a type of ‘amalgam’ filter of all such sources, is that contained in analyst reports. Many researchers suggest that analyst reports are the

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8There exists a host of literature on the permanent and transitory earnings components in forecasting earnings per share (Piotroski and Roulstone, 2004; Jones, Morton and Schaefer, 2000; Baber, Kang and Kumar, 1999; Ali and Zarowin, 1992a, Ali and Zarowin, 1992b; Ali, Klein and Rosenfeld, 1992; Collins and Kothari, 1989; Ou and Penman, 1989; Kormendi and Lipe, 1987; Beaver, Lambert and Morse, 1980). In our study we do not disentangle the permanent component from the transitory component. In fact, a priori, our model should work much better if we confine our analysis to the permanent component of the earnings, both reported and forecast. Our study is different in that it does not rely on the share price of the firm to test the value relevance of the earnings of a firm.
main and most credible alternative source of competing information to actual earnings reports (see Frankel, Kothari and Weber, 2006; Asquith, Mikhail and Au, 2005). Why? Analysts are not hindered by limitations of earnings reports such as timeliness and adherence to GAAP. Moreover, analysts are able to capture and process with skill the many and varied information signals available, as well as extract other information not readily available in the public domain.

Francis, Schipper and Vincent (2002) directly examine analyst reports as the primary source of competing information and whether they reduce the usefulness of reported earnings, as measured by the market price reaction to the earnings announcement. In their main tests, they examined both mean and aggregate absolute abnormal return (AAR) for both analyst reports and earnings announcements related to a particular financial year.\(^9\) They found that the AAR for analyst reports is positively associated with the AAR for the earnings announcements and conclude that this is consistent with analyst reports complementing earnings announcements. Furthermore, they examine the relationship between current period earnings announcements and the subsequent year analyst reports. They found some evidence that earnings reports in the current year are positively associated with the market reaction of analyst reports in the following year. They conclude that this may be consistent with analyst reports being a

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\(^9\) According to Francis et al (2002, p. 314), “Aggregate AAR’s are constructed by summing all AARs to all analyst reports about firm j disclosed prior to firm j’s earnings announcement. For the mean AARs, it is constructed by averaging the aggregate AARs over the number of earnings announcements or the number of analyst reports in a given year.”
complementary information source rather than a substitutionary information source to earnings announcements.\(^\text{10}\)

Asquith, Mikhail and Au (2005) examine analysts’ reports and the market reaction to the release of the reports. They found that analysts provide new information and interpret previously released information. In addition, they also found that the market reacts to all of the elements of the report, namely, earnings forecast revisions, recommendation revisions, and price target revisions. They also concluded that analyst reports play a role in interpreting information from other sources.

Frankel, Kothari and Weber (2006) examine the cross-sectional determinants of the informativeness of analysts research by examining the share price impact of analyst reports, controlling for endogeneity among factors that may contribute to the information environment. Their findings are that analysts’ reports are informative, that the information environment affects the informativeness of the reports and that the informativeness of analyst research and financial statements are complementary.

Another strand of the literature on the relationship between earnings information and analyst information is the theoretical work of Kim and Verrecchia (1991, 1994 and 1997). The main feature of their work is the modelling and predictions of market reactions to public announcements. Notably, their models recognise and attempt to incorporate the interaction of public and private information. They identify institutions such as financial analysts and large shareholders (e.g. fund managers) who are capable of acquiring and processing information in such a way that it retains a private/confidential nature. In this setting, Kim and Verrecchia model how the quality or precision of the

\(^{10}\text{Cheng (2005) concludes, on research in a related area, that analysts do use information contained in financial reports but do not fully incorporate all this information into their forecasts of future earnings. In addition, analysts draw on information beyond that contained in financial reports.}\)
forthcoming public announcements affect the incentives and acquisition of private information by these institutions. Public announcements of sufficient precision, which permit traders to act profitably on the acquired private information, will further affect the acquisition of private information by these institutions. In addition, their model predicts that as the quality of prior information increases or as the cost of information gathering increases, the incentive to acquire costly private information will decrease. If we interpret analyst reports as revealed private information, their models appear to suggest that as the quality of earnings announcements increase, then prior earnings are sufficient signals for future earnings. This sufficiency suggests that there is less incentive and a lower need for the acquisition of useful private (analyst) information. As such, it may result in the analysts reports which nevertheless are produced, to simply “repeat” the information contained in public earnings announcements. Further, as the (relative) cost of information gathering decreases (inversely correlated with the size of the company) and holding all other factors constant, their model indicates that analyst reports may become substitutes for earnings announcements.

Lang and Lundholm (1996) find that more informative corporate disclosures are positively related with the number of analyst forecasts and negatively related to analyst forecast dispersion. Lang and Lundholm (1996, p. 490) conclude that “disclosures increase the demand for analyst reports because they reduce the costs of supplying them”. They argue that their evidence may show that analysts are not directly competing with the firm’s disclosures and may be “consistent with the view that analysts possess both firm-provided and privately-acquired information” (p. 490). Barron, Byard and Kim (2002) also find evidence that the demand for analyst reports increases with the firms’
disclosures. They argue that their findings and those of Lang and Lundholm (1996) are consistent with the fact that analysts serve as information processors and analyst reports are complements to actual earnings reports.

2.3 Hypotheses

The main theme from the preceding literature review is that there are many competing, complementary or even substitutionary sources of information, about the future earnings of firms. Our paper focuses on a particularly important source of such information: analyst earnings forecasts.

Emanating from the preceding discussion, our hypotheses are premised on the idea that analysts’ earnings forecasts will (depending on their quality) successfully predict the next round of (scheduled) earnings numbers. In turn, we hypothesise that past (scheduled) reported earnings numbers contain information that is extremely useful to analysts, thereby having a major impact on the forecasts that they make of future earnings. Accordingly, we set up a framework which accommodates the possibility of uni-directional or bi-directional “causality” between reported earnings and analyst earnings forecasts.

Our hypotheses are as follows:

**H1**: Analysts forecasts of earnings contain information (additional to that contained in past forecasts) that is useful for predicting earnings (i.e. forecasts Granger “cause” reported earnings)
**H2:** Prior reported earnings numbers contain information (additional to that contained in past forecasts) that is useful for future forecasts (i.e. earnings report Granger “cause” analysts forecasts)

The first hypothesis is tested against the null that forecasts do not Granger cause earnings, while the second is tested against the null that earnings do not Granger cause forecasts. If the null is rejected in each case, then we can conclude that there is bi-directional causality, and if we fail to reject the null in each case then there is no evidence of causality in either direction.

We stress that the interpretation of (Granger) causality in this context is not literal. Rather, it has the interpretation that is common in the forecasting literature, which simply means that if X Granger causes Y, then past values of X provides information (over and above that contained in past values of Y) that is useful for predicting Y. Causality tests are interesting in this context because they condition on a given information set (e.g., past earnings) and then ask if other information (e.g., past forecasts) improves the ability to predict a target variable (e.g., future earnings). The conditioning on one portion of the information set allows the researcher to assess the contribution that another portion of the information set makes towards the forecast, and this is particularly useful if one wants to follow information flows from one variable to another.

Our tests seek to examine directly the time series relationship between analysts’ earnings forecasts and actual earnings announcements, in addition to simply asking whether analysts’ forecasts are a credible and sufficiently accurate source of timely competing information to the reported earnings event. The key innovation in our study is that we assess information flows between earnings and forecasts, using a robust and
widely acclaimed time series approach that is independent of any share market consequences. Is so doing, we complement and extend the cross-sectional methodologies used in prior studies which have examined the information dynamics of earnings.

3. Data and Sampling Issues

3.1 Basics

The typical US firm furnishes an earnings report that relates to each quarter \( t \) and for each of these reports, we record actual earnings per share \( (e_t) \), the date \( s_t \) on which the earnings report was issued. Analysts' forecasts of earnings per share \( (f_{jt}, \text{ for analysts } j = 1,2,\ldots,J_t) \), and the date \( \tau \) on which analyst \( j \) issued the forecast for quarter \( t \) are also recorded. Both of these are sourced from the I/B/E/S database. The original dataset consisted of information relating to 19,983 firms, over the period from January 1, 1984 to June 30, 2005. In total, there were 1,679,916 forecasts relating to 467,462 quarterly earnings reports, so that on average we had 23.4 quarterly earnings reports for each firm, and 3.6 earnings forecasts for each actual earnings event. We have a maximum of 86 quarterly earnings reports for each firm and up to 225 earnings forecasts relating to each actual report.

Given that we wish to trace the dynamics of information flows from reported earnings to earnings forecasts (and vice-versa), we give special attention to the timing of forecasts, relative to when the relevant quarter ended and when the associated earnings report was actually issued. The average lag between timing of the earnings report due date and when it was issued was 33.2 days. While most forecasts for any given quarter were made during that quarter, some were made prior to the beginning of the quarter in
question, and many were made after the end of the quarter but before the earnings report was actually issued. As such, we characterize our sample of earnings forecasts into three mutually exclusive groups: *Type 1* forecasts are forecasts which occur prior to the release of reported earnings for the previous quarter; *Type 2* forecasts are forecasts that occur within the quarter in question, but post *Type 1* forecasts; while *Type 3* forecasts are those that come after the end of the quarter, but prior to the actual reported earnings event.\(^\text{11}\)

Figure 1 provides a pictorial representation of the three different types of forecast.

[Figure 1 about here]

Figure 2 shows the distribution of earnings forecasts for Marsh and McClennen during the first quarter of 1985, as an illustrative example of a typical situation in our sample. In this case there were a total of nine forecasts. Two of these forecasts were made before the release (on January 31 1985) of the report for the fourth quarter 1984 earnings, five forecasts were made between the release of the fourth quarter report and the end of the first quarter of 1985, two forecasts were made between the end of the first quarter 1985 and the release of the corresponding report on April 30 1985, and one forecast was made after the release of the report.

[Figure 2 about here]

We treat each of these types of forecasts differently, because each is associated with a different information setting. The earliest (*Type 1*) forecasts (labelled as section ‘T1’ in the figure) do not account for 1984:4 earnings that were announced on January 31 1985. *Type 2* forecasts (in the section labelled ‘T2’) incorporate the announced 1984:4 earnings, \(^\text{11}\) Interestingly, the timing of *Type 3* forecasts corresponds to the period designated for earnings “preannouncements” i.e. management forecasts made after the end of the reporting period, but before the release of the preliminary final earnings announcement. For examples of this literature, see Skinner (1994); Soffer, Thiagarajan and Walther (2000); and Skinner and Sloan (2002). In the latter part of our sample period, the existence of preannouncements may have a substantial impact on the *Type 3* analyst forecasts.
but occur prior to the quarter’s end. *Type 3* forecasts (in the section labelled ‘T3’) incorporate the information in the *Type 1* and *Type 2* forecasts, as well as all information that has come to hand before the end of 1985:1.12

Of the 19,983 firms in our original sample, there were only one hundred and twenty two for which we had a continuous series of at least 60 actual reported earnings observations, and we restricted our time series analysis to these firms. Summary details of the reported earnings and associated forecasts for these firms are displayed in Table 1. The restricted sample contains 9,078 observations and 126,202 forecasts. Most (80.1%) of these forecasts of the *Type 2* variety – they are issued after the last earnings announcement, but before the end of the reporting quarter. An additional 17.4% of the *Type 3* variety – they are forecasts issued after the quarter has ended but before the earnings report is actually made public.

[Table 1 about here]

### 3.2 Are analyst forecasts unbiased?

The lower half of Table 1 contains some statistics relating to the accuracy of the forecasts. Overall, there is a statistically significant positive bias in the forecasts, consistent with analyst optimism, particularly with respect to *Type 1* forecasts, which are made well in advance of the released earnings report. Interestingly, the forecasts made after the end of the reporting quarter are negatively biased, implying a small positive earnings surprise once the earnings are actually announced. The bottom portion of Table 1 shows the correlations between the absolute value of the forecast errors and the time (in

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12 The final region of forecasts in Figure 2 (labelled ‘T4’) can potentially incorporate all relevant information, including the announced earnings. However, since reported earnings are known, these are not valid forecasts in the normal sense of the word – thus we ignore them for the purposes of our analysis.
days) until the earnings for the target quarter are actually announced. Here, the correlation is strongest for *Type 3* forecasts, consistent with forecast errors being smaller (in absolute magnitude) as the forecast horizon becomes smaller. It is interesting to note that *Type 1* forecasts occur so far in advance of the release of announced earnings that the associated forecast errors have no significant correlation with the forecast horizon.

An across the board regression of reported earnings on analysts’ forecasts produces the following outcome:

\[
\hat{\epsilon}_t = -0.0008 + 0.9851 f_t \quad \text{with} \quad R^2 = 0.864 \quad \text{and} \quad N = 126202.
\]

(\(-0.217\) \quad (100.6))

The figures in parentheses are heteroskedasticity and autocorrelation covariance corrected (HAC) t-statistics, and separate tests of the null hypotheses that the intercept is zero (\(\beta_0 = 0\)) and the slope coefficient is unity (\(\beta_1 = 1\)) have p-values of 0.8358 and 0.1285, respectively. Thus the forecasts initially appear to be unbiased, although a joint test of these hypotheses contradicts this conclusion, having a p-value of 0.0012. Repeating this regression for each of the 122 firms, leads to 45 rejections of the null hypotheses that \(\beta_0 = 0\), 45 rejections of the null that \(\beta_1 = 1\), and 75 rejections of the joint null. This shows that although forecasts are unbiased for about 40% of the firms in our sample, there is evidence of bias in the remaining 60%.

An across the board regression of earnings on the three forecast types (with the three types of forecasts being dummied using \(d_{1t}, d_{2t}, \text{and} \ d_{3t}\)) produces the following outcome:

\[
\hat{\epsilon}_t = -0.011d_{1t} - 0.002d_{2t} - 0.006d_{3t} + 0.896 \ d_{1t}f_t + 0.981 \ d_{2t}f_t + 1.011 \ d_{3t}f_t,
\]

(\(-0.99\) \quad (\(-0.05\)) \quad (\(-0.12\)) \quad (21.84) \quad (92.34) \quad (97.74))
As above, the brackets contain HAC t-statistics. In this case, the null hypothesis that the three forecast types are equally as accurate is soundly rejected. The null hypothesis that forecasts are jointly unbiased is soundly rejected, as are the null hypotheses that the Type 1 and Type 2 forecasts are unbiased. However, the data accepts the restriction that the Type 3 forecasts are unbiased, with the p-value for the relevant test being 0.1775.\(^\text{13}\)

3.3 Organising the analyst forecasts

The broad research questions of interest are whether analysts' earnings forecasts represent useful substitutes or complements to actual reported earnings, and what sort of lead-lag structures characterise the relationship between the forecasts and the reports. In particular we are interested in whether there is information in the earnings forecasts/(reported earnings) that is useful for predicting reported earnings/(earnings forecasts), and whether the forecasts/(reports) contain information that is not contained in past reports/(forecasts).

Two time series techniques that are often used to address issues such as these are Granger causality tests and forecast encompassing tests.\(^\text{14}\) However, each of these tests are typically based on regularly observed data, with each series being observed (just once) during each time period. In the current setting however, we have to deal with the fact that there may be many forecasts for each earnings observation, and that forecasts and earnings are not observed contemporaneously.

We appeal to the forecast combination literature to address the first of these issues (see Timmermann, 2006), and work with "combined" or consensus forecasts for each quarter. There are many ways of combining forecasts and while there is an ongoing

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\(^{13}\) Details are not reported to conserve space.

\(^{14}\) Currently, we only address the Granger-causality type tests.
debate regarding which combinations are optimal, it is widely recognised that arithmetic averages work well in many situations. Indeed, arithmetic averages are often superior (in terms of root mean squared error) to trimmed averages or averages that have been weighted according to criteria such as the relative timing of forecasts. This leads us to choose unweighted forecast averages for each quarter as our representative measure.

However, we do allow for the forecast timing considerations alluded to above by considering three forecast combinations. First, using $d_{2t}$ as an indicator taking a value of unity when $f_{jtr}$ is a Type 2 forecast and zero otherwise, we focus on $f_{2t}$ defined below, as our primary forecast variable:

$$f_{2t} = \frac{1}{\sum d_{2t}} \sum_{j=1}^{J_t} (f_{jtr} \times d_{2t})$$ (1)

This forecast metric takes the arithmetic average of Type 2 forecasts, across analysts for a given company, in a specific quarter. Type 2 forecasts are "standard" forecasts, in the sense that while they might incorporate past earnings information, they don't incorporate any information that becomes available after the end of the reporting period.

Alternatively, we also calculate:

$$f_{12t} = \frac{1}{\sum d_{12t}} \sum_{j=1}^{J_t} (f_{jtr} \times d_{12t})$$ (2)

$$f_{23t} = \frac{1}{\sum d_{23t}} \sum_{j=1}^{J_t} (f_{jtr} \times d_{23t})$$ (3)

$$f_{123t} = \frac{1}{\sum d_{123t}} \sum_{j=1}^{J_t} (f_{jtr} \times d_{123t})$$ (4)

for comparison and robustness checks. In the first case, $d_{12t}$ picks out Type 1 or Type 2 forecasts, $d_{23t}$ picks out Type 2 or Type 3 forecasts, while $d_{123t}$ picks out forecasts of
Type 1, Type 2 or Type 3. Each metric is the arithmetic average for the designated forecast types, across analysts for a given company, in a specific quarter.\(^{15}\)

Figure 3 compares the three forecast combinations for a typical firm, Lilley Eli. We find that there is very little difference between them, and since the naked eye cannot differentiate them from each other when they are plotted in the same graph, we have added constants to each of \(f_{12}\) and \(f_{123}\) to illustrate their co-movement. Figure 4 compares the combination \(f_{2}\) forecast with the reported earnings series for the same illustrative company. The forecasts track the reported earnings quite closely, although not surprisingly they fail to capture the sharp decline in earnings in 1987:4. In this case we can attribute the forecast error to analysts' inability to anticipate the 1987 stock market crash. Such ‘failures’ were observed for several (but not all) firms for this quarter, and similar failures at other times were observed once or twice for most of the sample.

[Figures 3 and 4 about here]

Table 2 reports the time series properties of earnings and forecast combinations. It shows that for most of the one hundred twenty two firms in our sample, there is a quarterly seasonality in the data series and evidence of trend. Much of this trend is likely to be drift associated with a unit root process in earnings, because the unit root tests reported in column 7 reject the null of a unit root in only twenty two cases. Data that contains a unit root with drift is “non-stationary” in the sense that even if it is detrended, the detrended data has a non-constant mean so that it “wanders” rather than returns to trend. The variance is also non-constant, growing with the sample size. These properties

\(^{15}\) We did not calculate forecast averages for Type 1 or Type 3 forecasts alone because on several occasions the set of forecasts relating to any given reported earnings observation did not include any of these types of forecasts.
can imply that standard t and F tests statistics don’t have the usual t and F distributions, so that care is needed when attempting to draw inference based on the usual sorts of tests. We deal with this problem in the formal analysis that follows. The properties of the forecasts mirror those for earnings, although there are differences between the incidence of outliers in the earnings series and the incidence of outlying forecasts.

[Table 2 about here]

Table 3 provides some preliminary analysis of the relationship between reported earnings and earnings forecast combinations. The usual tests of "good forecasting" are provided in column 4, though it needs to be noted that the time series behaviour of our raw data is likely to invalidate many of these tests. Nevertheless, if we treat these test results as "indicative", then we find evidence against the assertion that $e_t = f_t + \text{a zero mean prediction error}$, for about thirty out of the one hundred and twenty two firms. Given that earnings and forecasts appear to contain unit roots, an appropriate way to analyse the relationship between them is to consider whether they are cointegrated. Series with unit roots are often called integrated series in the time series literature, and two integrated series are cointegrated if they move together in the long run, even though each series tends to “wander” when considered individually. The idea that there might be a close long-run relation between earning and forecasts is intuitively appealing, and it is actually expected in a forecasting context.\footnote{Campbell and Shiller (1988) discuss this issue in the context of forecasting dividends.} In column 5, tests of no cointegration support cointegration in most cases, and if we force the cointegrating vector to reflect a
one-to-one relationship between earnings and forecasts, then the tests (in column 6) broadly support this restriction.\footnote{Formally, the tests are performed using the augmented Dickey-Fuller approach. In this case, the rejection of a unit root supports cointegration and a long run relationship between earnings and forecasts.}

4. Tests of Granger Causality – modified to account for irregular observations

4.1 Standard Granger Causality tests

Given two series $x_t$ and $y_t$, standard Granger Causality tests (Granger, 1969) are based on the bivariate system given by:

\[
x_t = c_x + \sum_{j=1}^{p} \alpha_j x_{t-j} + \sum_{j=1}^{p} \beta_j y_{t-j} + \epsilon_{xt} \quad (5)
\]

\[
y_t = c_y + \sum_{j=1}^{p} \gamma_j x_{t-j} + \sum_{j=1}^{p} \delta_j y_{t-j} + \epsilon_{yt}
\]

and a test that $X_t$ does not Granger cause $Y_t$ (i.e. $H_0 : X_t \not\rightarrow Y_t$) is an F-test of $H_0$: all $\gamma_j = 0$, while a test that $Y_t$ does not Granger cause $X_t$ is an F-test of $H_0$: all $\beta_j = 0$. Granger is careful to emphasize that a rejection of $H_0$: $X_t \not\rightarrow Y_t$ does not mean that $X_t$ might cause $Y_t$ in any physical sense, rather he stresses the forecasting implications that the history of $X_t$ (i.e. $X_t^H = \{x_{t-1}, x_{t-2}, \ldots, x_t\}$) must contain information that is not contained in $Y_t^H = \{y_{t-1}, y_{t-2}, \ldots, y_t\}$, and that this additional information is useful for predicting $y_t$. Similarly, a rejection of $H_0$: $Y_t \rightarrow X_t$ simply means that $Y_t^H$ contains information (not in $X_t^H$) that is useful for predicting $x_t$. Practical considerations in conducting these tests include the choice of the lag length $p$ (conventionally achieved using information criteria
such as AIC), and checking that $x_t$ and $y_t$ do not have properties (such as unit roots) that might cause the distribution of the test statistic to be non-standard (i.e. not an F distribution).

The latter problem can be circumvented by using an approach outlined in Toda and Yamamoto (1995) or by considering an error correction approach. Toda and Yamamoto’s procedure simply adds an extra lag onto (5), but conducts the tests on lags 1 – p. Standard t and F tests are valid once the extra lag has been included in the test regression. The second and more common approach is based on the well known error correction re-parameterization of (5) given by:

\[
\Delta x_t = c_x + \lambda_x (x_{t-1} - \pi_x y_{t-1}) + \sum_{j=1}^{p-1} a_j^* \Delta x_{t-j} + \sum_{j=1}^{p-1} \beta_j^* \Delta y_{t-j} + \epsilon_{xt} \tag{6}
\]

\[
\Delta y_t = c_y + \lambda_y (y_{t-1} - \pi_y x_{t-1}) + \sum_{j=1}^{p-1} \gamma_j^* \Delta x_{t-j} + \sum_{j=1}^{p-1} \delta_j^* \Delta y_{t-j} + \epsilon_{yt}
\]

where $\lambda_x = \sum a_j - 1$, $\pi_x = \sum \beta_j / \lambda_x$, and the $\alpha_j^*, \beta_j^*$ fill out the remaining lag structure. Equation (6) is obtained from (5) by subtracting $(x_{t-1}, y_{t-1})'$ from each side of the equation and rearranging terms. In equation (6), $\pi_x$ measures the long-run impact of $y_t$ on $x_t$, and $\pi_y$ (=1/$\pi_x$) measures the long-run impact of $x_t$ on $y_t$. If $x_t$ and $y_t$ are cointegrated then a cointegrating relationship is given by $x_t = \pi_y y_t$ and at least one of $\lambda_x$ or $\lambda_y$ will be non-zero, but (6) is a valid representation of (5) even if $x_t$ and $y_t$ are not cointegrated. Tests based on the equations in (6) are well behaved because the variables in these equations are typically stationary. Exceptions occur when there is no long-run relationship between $x_t$ and $y_t$, so that $x_{t-1} - \pi_y y_{t-1}$ is non-stationary. In this case OLS will
force $\hat{\lambda}_x$ and $\hat{\lambda}_y$ to zero so as to minimise the sum of squared residuals, but the remaining parameter estimates are well behaved.

Three types of Granger causality tests are typically considered in this framework: (i) a test of long-run Granger causality (LRC); (ii) a test of short-run Granger causality (SRC) and (iii) an overall test of Granger causality (GC). Considering tests that $y_t$ does not Granger cause $x_t$, the long-run test is a (t or F) test of $H_0: \lambda_x = 0$; the short-run test is a test (F-test) of $H_0: \beta_j^* = 0$, and the overall test is a joint test of both of these hypotheses. The mirror image of these tests apply for the converse case of $x_t$ does not Granger cause $y_t$.

Modified Granger causality tests

Our time series for reported earnings and their forecasts do not quite conform with the above framework, because our forecasts $f_t$ are measured before the earnings $e_t$ are observed. Further, we are interested in whether $\{f_t, f_{t-1}, f_{t-2}, \ldots f_1\}$ contains information about $e_t$, over and above the information in $\{e_{t-1}, e_{t-2}, \ldots e_1\}$, whereas a standard Granger causality analysis asks whether $\{f_{t-1}, f_{t-2}, \ldots f_1\}$ contains information about $e_t$, over and above the information in $\{e_{t-1}, e_{t-2}, \ldots e_1\}$. That is, in our framework $f_t$ is validly included as part of the information set for $e_t$, whereas it would not be included in conventional settings. We are also interested in whether the history of earnings provides information (not in past forecasts) that feeds into current forecasts, i.e. whether $\{e_{t-1}, e_{t-2}, \ldots e_1\}$ contributes to forecasts $f_t$, given that $\{f_{t-1}, f_{t-2}, \ldots f_1\}$ is known. This leads us to consider the system specified by:

$$e_t = c_e + \sum_{j=1}^{p} a_j e_{t-j} + \sum_{j=0}^{p-1} \beta_j f_{t-j} + \epsilon_{et}$$

(7)
\[ f_t = c_f + \sum_{j=1}^{j=p} \gamma_j e_{t-j} + \sum_{j=1}^{j=p} \delta_j f_{t-j} + \epsilon_f \]

and its error correction parameterization given by

\[ \Delta e_t = c_e + \lambda_e \left( e_{t-1} - \pi_x f_{t-1} \right) + \sum_{j=1}^{j=p-1} a_j \Delta e_{t-j} + \sum_{j=0}^{j=p-2} \beta_j \Delta f_{t-j} + \epsilon_e \]  \tag{8}

\[ \Delta f_t = c_f + \lambda_f^* \left( e_{t-1} - \pi_x f_{t-1} \right) + \sum_{j=1}^{j=p-1} \gamma_j^* \Delta e_{t-j} + \sum_{j=1}^{j=p-1} \delta_j^* \Delta f_{t-j} + \epsilon_f \]

where we have normalised the error correction terms on \( e_t \) (and rescaled \( \lambda_f \) accordingly).

Tests of whether earnings forecasts lead reported earnings in the long run are based on \( \lambda_e \), tests of whether forecasts lead earnings in the short run are based on the \( \beta_j^* \), and overall tests of whether forecasts lead earnings are joint tests on \( \lambda_e \) and \( \beta_j^* \). Similarly, tests of whether past reported earnings provide information about current forecasts that is not contained in past forecasts, are tests relating to \( \lambda_f^* \) and/or \( \gamma_j^* \).

We call our tests Granger causality tests, but emphasise that they have a subtly different format and interpretation than standard Granger causality tests. In our empirical implementation, we choose the lag length \( p \) by applying AIC to the joint system defined in (7). AIC is useful in this context, because it tends to choose long lag lengths, which then increases the likelihood that our models incorporate all relevant dynamics (that are needed for forecasting) and reduces the possibility of serial correlation in the residuals. We augment our chosen lag length for (7) by one so that we can use the Toda Yamamoto (1995) results and have confidence in our inference. We include quarterly dummies in (7) and (8) to account for the seasonality reported in Table 2, and we include a time trend in (7) to account for possible drift. When estimating the equations in (8) we use a two-stage approach in which we first estimate the "error correction term" or deviation from the long
term relationship (i.e. \( z_t = e_t - \pi f_t \)), and then use the implied \( z_{t-1} \) and single equation OLS to estimate our "causality" coefficients. We experiment with two estimates of \( z_t \); the first \( (z_t^1) \) works with the residuals obtained by running a regression of \( e_t \) on \( f_t \) (and a constant), while the second is the "theoretical deviation", defined by \( z_t^2 = e_t - f_t \). We base all of our causality analysis on HAC corrected F-tests.

5. **Empirical Results**

Table 4 presents summary information relating to our estimates of the equations in (7) for each of the one hundred and twenty two firms. Reported regressions are based on Type 2 forecasts (i.e. we set \( f_t = f_{2t} \)), combined Type 1 & 2 forecasts in which \( f_t = f_{12t} \), combined Type 2 & 3 forecasts in which \( f_t = f_{23t} \), and all types in which \( f_t = f_{123t} \). The first thing of note is that there was very little difference in the results found between these four sets of forecasts.

Nearly all of the equations fit the data very well, with most \( R^2 \) measures around 90%. In columns 3 and 5 we present the results of "Granger causality" tests based on the \( \beta \) and \( \gamma \) coefficients, to provide a preliminary indication of the causality structure in the data. The reported \( p \)-values suggest that past forecasts are useful for predicting current earnings in all but fifteen (two) firms for Type 2 forecasts (all types of forecasts). Also, analysts incorporate information from past earnings in their forecasts. Indeed, for Type 2 \( (Type 1 & 2) \) forecasts, there are only twenty three (twenty two) cases in which analysts don't seem to be using information on past earnings when forming their forecasts. By comparison, for Type 2 & 3 forecasts, the number of cases in which analysts do not seem to be using information on past earnings has grown to twenty seven cases.
Details on the chosen lag structure for these models are not reported, but our results show that although the persistence in earnings and forecasts varies quite widely from firm to firm, it is generally long-lived. Past information takes three years (12 quarters) to be fully reflected in current data in more than one third of our companies. This is particularly noteworthy given that the previous accounting literature has found or assumed much shorter persistence in earnings numbers, but it is quite consistent with Ou and Penmen’s (1989) notion of a permanent component in earnings.

[Table 4 about here]

Tables 5 and 6 present details relating to estimated versions of the re-parameterised system (8). In both tables, each of the two error correction models lead to very similar outcomes and it is noteworthy that the overall tests of no Granger causality in Tables 5 and 6 are also similar to those in Table 4. For the first differences in reported earnings equations in Table 5, the results for the estimated error correction term suggest a long-run effect of Type 2 (all types) forecasts in fifty eight (sixty nine) cases.\(^{18}\) The estimated \(\lambda_e\) coefficient while not reported, is usually negative for every firm. From this we can infer that on average, changes in reported earnings will fall when previous forecasts were too low \((e_{t-1} - f_{t-1} > 0)\) and they will rise (on average) when past forecasts were too high. First differences in earnings forecasts also have short-run predictive power for quarterly changes in reported earnings. For Type 2 (all types) forecasts, the results suggest a short-run effect for one hundred and eight (one hundred and twenty) cases.

[Tables 5 and 6 about here]

---

\(^{18}\) We find similar results for the case in which there is imposed error correction term.
For the quarterly changes in earnings forecast shown in Table 6, we see less evidence of both long and short-run causality, although it is still clear that past earnings generally contain information that appears to influence forecasts. Announcements appear to contain useful long-run information about forecasts. The results of the imposed error correction term set-up are generally stronger than the counterpart estimated error correction term results. For example, in the imposed situation with Type 2 forecasts, there is a long-run causality effect in fifty four cases, compared to thirty seven when the error correction term is estimated. For cases when the estimated $\lambda_f^*$ is statistically significant, it is generally positive, reflecting future upward adjustment of forecasts when past earnings were higher than predicted ($e_{t-1} - f_{t-1} > 0$).

Finally, the results of short-run causality are stronger than for the long run. For example, an examination of the imposed error correction term results show that for seventy two cases for the Type 2 forecasts there is evidence of short-run causality, whereas only fifty four counterpart cases of long-run causality are found.

6. Conclusion

We examine time series of analyst earnings forecasts and reported earnings for their information content by using a non-standard Granger causality test. Our work contributes to the accounting literature by using an alternative approach to study information flows that is not reliant on the market reaction of firms on the forecast or earnings announcement dates. In preliminary analysis we find evidence that lags associated with information flows are longer (up to twelve quarters) than has been assumed in the empirical literature and we reconfirm the evidence that supports a positive bias in forecasts, although this evidence becomes weaker as the forecast horizon becomes shorter.
By developing non-standard Granger causality tests that can be used when observations are irregularly spaced, we find that analysts’ earnings forecasts Granger-cause reported earnings for nearly all firms in the short run and for about half the firms in the long run. This provides strong evidence that forecasts are useful for predicting future earnings despite a possible forecast bias.

We also find that earnings Granger-cause forecasts for about two thirds of the firms in the short run and for about one third of the firms in the long run. Though there is evidence that earnings information is reflected in future forecasts (i.e. earnings complement forecasts), this is not always the case.
References


Sequeira, JM, Y. K. Ho, and T. L. Tang, 2006. Earnings surprises, asymmetry of returns and market level changes – An industry level study, forthcoming in *Journal of Accounting, Auditing and Finance*.


<table>
<thead>
<tr>
<th>Properties</th>
<th>All Forecasts</th>
<th>Type 1</th>
<th>Type 2</th>
<th>Type 3</th>
</tr>
</thead>
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<td>3,087</td>
<td>101,112</td>
<td>22,003</td>
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<td>0.0460***</td>
<td>0.0080***</td>
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<td>0.0091</td>
<td>0.0019</td>
<td>0.0025</td>
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<td>f - e</td>
<td>, (s - τ))</td>
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<td>0.0180</td>
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</table>

Notes:
The symbols *** and * signify statistically significant at the 1% and 10% levels respectively. The quantity $(s - τ)$ measures the time between when the forecast was made and when the report was issued. HAC standard errors are corrected for heteroskedasticity and autocorrelation.
Table 2: Properties of Time series for Reported Earnings and Earnings Forecast Combinations

<table>
<thead>
<tr>
<th>Earnings / Forecast Type</th>
<th>Ave $R^2$</th>
<th>No. of Outliers</th>
<th>Number of Rejections (at 5% level)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
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<tr>
<td>Type 1 &amp; Type 2</td>
<td>0.5322</td>
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<td>4</td>
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<tr>
<td>Type 2 &amp; Type 3</td>
<td>0.5168</td>
<td>27</td>
<td>1</td>
</tr>
<tr>
<td>All Forecasts</td>
<td>0.5593</td>
<td>6</td>
<td>2</td>
</tr>
</tbody>
</table>

Notes: Time series properties reported in this table relate to a sample of 122 firms. All columns except the last relate to the regression: $y_t = \alpha_0 t + \alpha_1 q_1 + \alpha_2 q_2 + \alpha_3 q_3 + \alpha_4 q_4 + u_t$, where $y_t$ is the series of interest, $t$ is a time trend and the $q_i$ are quarterly dummies. Forecasts are separated into three types according to their timing relative to the quarter to which they relate. Type 1 forecasts occur prior to the release of reported earnings for the previous quarter; Type 2 forecasts occur during the quarter, but post Type 1 forecasts and Type 3 forecasts occur after the end of the quarter but before the reporting date of the earnings. Outliers are assessed relative to 6 standard error limits at either extreme.

Table 3: Relationship between Reported Earnings and Earnings Forecast Combinations

<table>
<thead>
<tr>
<th>Forecast Type (1)</th>
<th>Ave $R^2$</th>
<th>$H_0: \beta_1 = 1$</th>
<th>$H_0: \beta_0 = 0 &amp; \beta_1 = 1$</th>
<th>$e_t - \beta f_t$</th>
<th>$e_t - f_t$</th>
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</thead>
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<td>Type 2</td>
<td>0.7118</td>
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<td>31</td>
<td>87</td>
<td>100</td>
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<td>Type 1 &amp; Type 2</td>
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<td>26</td>
<td>31</td>
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<td>98</td>
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<td>Type 2 &amp; Type 3</td>
<td>0.7714</td>
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<td>30</td>
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<td>All Types</td>
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<td>23</td>
<td>29</td>
<td>98</td>
<td>98</td>
</tr>
</tbody>
</table>

Notes: Information reported in this table relate to a sample of 122 firms. All columns except the last relate to the regression: $e_t = \beta_0 + \beta_1 f_t + u_t$, where $e_t$ is reported earnings and $f_t$ is the earnings forecast. Forecasts are separated into three types according to their timing relative to the quarter to which they relate. Type 1 forecasts occur prior to the release of reported earnings for the previous quarter; Type 2 forecasts occur during the quarter, but post Type 1 forecasts and Type 3 forecasts occur after the end of the quarter but before the reporting date of the earnings.
Table 4: Predictability of Reported Earnings and Earnings Forecasts

<table>
<thead>
<tr>
<th>Forecast Type</th>
<th>Ave $R^2$ (2)</th>
<th>Rejections of $H_0$: $F$ does not Granger Cause $E$ (5 % level) (3)</th>
<th>Ave $R^2$ (4)</th>
<th>Rejections of $H_0$: $E$ does not Granger Cause $F$ (5 % level) (5)</th>
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</thead>
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<td>0.9113</td>
<td>107</td>
<td>0.8878</td>
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<td>0.9106</td>
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<td>Type 2 &amp; Type 3</td>
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<td>95</td>
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<td>All Types</td>
<td>0.9349</td>
<td>120</td>
<td>0.9312</td>
<td>93</td>
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</table>

Notes: Information reported in this table relate to a sample of 122 firms. Lag lengths $p$ were chosen using AIC for each bivariate system and then augmented by one. The earnings and forecasting equations are specified in equation (7) in the text, but they include quarterly dummies and a time trend as well. $H_0$: $F$ does not Granger Cause $E$ implies that all $\beta_j = 0$ and $H_0$: $E$ does not Granger Cause $F$ implies that all $\gamma_j = 0$. Forecasts are separated into three types according to their timing relative to the quarter to which they relate. Type 1 forecasts occur prior to the release of reported earnings for the previous quarter; Type 2 forecasts occur during the quarter, but post Type 1 forecasts and Type 3 forecasts occur after the end of the quarter but before the reporting date of the earnings. The test statistics have been calculated using HAC consistent covariances.

Table 5: Predictability of First Differences in Reported Earnings – Do Earnings Forecasts Granger Cause Reported Earnings?

<table>
<thead>
<tr>
<th>Forecast Type</th>
<th>Ave $R^2$ (1)</th>
<th>Estimated Error Correction Term</th>
<th>Number of Rejections (5 % level)</th>
<th>Ave $R^2$ (6)</th>
<th>Imposed Error Correction Term</th>
<th>Number of Rejections (5 % level)</th>
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<td>No LRC (2)</td>
<td>No SRC (3)</td>
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Notes: Information reported in this table relate to a sample of 122 firms. Lag lengths $p$ were chosen using AIC for each bivariate system. The earnings equation is the first of the two in equation (8) in the text. For the columns labelled “Estimated Error Correction Term” we replace the $(e_{t-1} – \pi f_{t-1})$ term by $z^1_{t-1}$, and for the columns labelled “Imposed ECT” we replace the $(e_{t-1} – \pi f_{t-1})$ term by $z^2_{t-1}$. See the text for definitions of $z^1_t$ and $z^2_t$. LRC stands for long-run Granger causality; SRC stands for short-run Granger causality and GC stands for overall (short-run and long-run) Granger causality. The test of $H_0$: no LRC implies $\lambda_e = 0$, the test of $H_0$: no SRC implies all $\beta^*_j = 0$ and the test of $H_0$: no GC implies $\lambda_e = 0$ and all $\beta^*_j = 0$. Forecasts are separated into three types according to their timing relative to the quarter to which they relate. Type 1 forecasts occur prior to the release of reported earnings for the previous quarter; Type 2 forecasts occur during the quarter, but post Type 1 forecasts and Type 3 forecasts occur after the end of the quarter but before the reporting date of the earnings. The test statistics have been calculated using HAC consistent covariances.
Table 6: Predictability of First Differences in Earnings Forecasts – Do Reported Earnings Granger Cause Earnings Forecasts?

<table>
<thead>
<tr>
<th>Forecast Type (1)</th>
<th>Estimated Error Correction Term</th>
<th>Imposed Error Correction Term</th>
<th>Number of Rejections (5% level)</th>
<th>Number of Rejections (5% level)</th>
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<td>No SRC</td>
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</table>

Notes:
Information reported in this table relate to a sample of 122 firms. Lag lengths $p$ were chosen using AIC for each bivariate system. The forecasting earnings equation is the second of the two in equation (8) in the text. For the columns labelled “Estimated Error Correction Term” we replace the $(e_{t-1} - \pi f_{t-1})$ term by $z^1_{t-1}$, and for the columns labelled “Imposed ECT” we replace the $(e_{t-1} - \pi f_{t-1})$ term by $z^2_{t-1}$. See the text for definitions of $z^1_{t}$ and $z^2_{t}$. LRC stands for long-run Granger causality; SRC stands for short-run Granger causality and GC stands for overall (short-run and long-run) Granger causality. The test of $H_0$: no LRC implies $\lambda^*_f = 0$ the test of $H_0$: no SRC implies all $\gamma^*_j = 0$ and the test of $H_0$: no GC implies $\lambda^*_f = 0$ and all $\gamma^*_j = 0$. Forecasts are separated into three types according to their timing relative to the quarter to which they relate. Type 1 forecasts occur prior to the release of reported earnings for the previous quarter; Type 2 forecasts occur during the quarter, but post Type 1 forecasts and Type 3 forecasts occur after the end of the quarter but before the reporting date of the earnings. The test statistics have been calculated using HAC consistent covariances.
Figure 1: Characterising Different Types of Analyst Earnings Forecast

Type 1 Forecasts

Type 2 Forecasts

Type 3 Forecasts

“Current” Quarter

Actual Reported Earnings for Previous Quarter

Actual Reported Earnings for “Current” Quarter
Figure 2: Forecasts for 1985 First Quarter Earnings
Marsh and McClennan

(○ indicates the forecasts, × indicates the reported earnings)

Earnings report released (30 April 1985) →
End of quarter (31 March 1985) →
Last quarter earnings report released (31 Jan 1985) →
Figure 3: Comparison of Forecast Combinations
(Lilley Eli Company)
Figure 4: Comparison of Earnings and f2 Combination Forecasts
(Lilley Eli Company)