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

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Abstract

We study information flows between earnings and forecasts, using suitably adapted Granger causality tests. This approach complements existing cross-sectional studies by abstracting from stock market reactions to information, and focussing on dynamic interactions between information flows instead. We find bi-directional causality in time-series of analyst earnings forecasts and reported earnings, supporting our expectation that forecasts contribute to information that is reflected in future reports. Further, our evidence of feedback suggests that past reports and forecasts are *both* reflected in future forecasts, implying that the information in reports has inherent value, and that forecasts do not fully substitute for 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 …. – we observe an '*earnings/forecasts*' cycle. 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 what are the dynamic interactions between earnings forecasts and firms' reported earnings in both the short-run and the long-run? Although our basic question is not new, the approach that we take is novel and the insight this offers is important.

The accumulated evidence that analysts provide a valuable service to investors, typically centres on the market price reactions to firm earnings announcements and analysts forecasts (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, it is recognized that the pooled cross-sectional approach and use of market reactions to support the information value of various competing sources of information (viz. analyst and firm 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 therefore open to debate and subject to a wide variety of interpretations.[1]

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[1]Notably, the post-earnings announcement drift evidence has been used to cast doubt on the efficiency with which the market responds to earnings news (see Bartov, Radhakrishnan and Krinsky, 2000; Ball and Bartov, 1996; Bhushan, 1994 and Bernard and Thomas, 1989, 1990). Also, a price drift similar to that observed for earnings announcements has been documented for analyst forecast revision announcements (see Gleason and Lee, 2003; Elgars, Lo and Pfeiffer, 2001 and Brennan, Jegadeesh and Swaminanthan, 1993). 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 paper explicitly models the (joint) *dynamic* characteristics of forecasts and earnings, seeking to establish whether the information contained in analyst forecasts is leading, contemporaneous or lagging a firm's public earnings announcement ('reported' earnings). We use an adaptation of standard Granger causality tests to achieve this aim.[2] Our application of this time series econometric procedure provides an alternative approach to the techniques that have been used in the extant literature, and offers new insights into the literature on the interaction between earnings and forecasts for the following reasons. First, our choice of a time-series framework affords us the unique opportunity to explore the temporal dimension of the earnings/forecasts interplay. Second, our analysis is conducted on a firm by firm basis, and therefore allows for firm specific differences in the evolution of earnings and forecasts. Third, we are careful to pursue our research objective without reference to stock price reactions. As such, our research method has the advantage of removing possible confounding effects that might have adversely influenced the conclusions drawn by previous studies: for example, the arbitrary choice of a returns window; the unknown degree of market efficiency/inefficiency; or the likely preferential treatment of some clients by analysts leading to information leakages. Finally, we differ from the prior literature because our focus is not on the short-run value relevance of information, but rather on whether or not information from different sources (i.e. from analysts or from reports) actually adds to existing information set on earnings.

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

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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.

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 stock price adjustments and vice versa.

In addition, there has been empirical evidence to suggest that the interaction between analyst forecasts and firm reported earnings is 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. [3] Specifically, management guide the analysts to certain earnings levels that avoid negative earnings surprises and this suggests that while analysts' revision announcements may pre-empt "public" earnings announcements, it does not necessarily mean that the analyst information is a substitute for earnings information. Earnings reports have intrinsic value because they provide an accountability function, a confirmation role, and evidence for (or against) careful and responsible management. Building on the earlier work of Skinner (1994) and Pownall, Wasley and Waymire (1993), recent studies on voluntary management earnings forecasts provide additional motivation for studying the timing, relevance and information content of different types of information (see Lennox and Park, 2006; Brown and Higgins, 2005).

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[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) examines 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. Finally, Matsumoto (2002) finds evidence that firms guide analysts' forecasts downwards to avoid missing expectations at earnings announcements.

In the US, there is a 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 are likely to have greater timeliness when compared to earnings and financial reports.[4]

Another branch of the empirical literature suggests asymmetric stock price reactions to falling short of versus beating analysts' consensus forecasts (Sequeira, Ho and Tang, 2007, Skinner and Sloan, 2002 and Lopez and Rees, 2001). While this evidence suggests that analysts' forecasts have significant information content, with wealth implications for management and investors, it also implicitly points to the relevance of earnings reports, which provide a yardstick for assessing whether forecasters have under or over-predicted earnings.

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. In this paper, our methodology addresses this interdependence by following the forecasts and actual earnings for each firm in chronological order, and exploring whether analysts' forecasts are a timely and accurate source of competing information in relation to reported earnings, and then whether reported earnings feed additional information into future forecasts. The fundamental questions that we investigate are: (i) are analysts' earnings forecasts substitutes, complements or simply a

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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.

repeat of reported earnings; and (ii) is there information in reported earnings that was not anticipated in past forecasts, but which contributes to future forecasts?

Addressing these questions 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 policies that govern the practices of and relationship between analysts vis-à-vis 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.

The results of our paper 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 (analysts forecasts) 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

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[5] As a recent example of regulators' interest in this general area, consider the SEC promulgation of Regulation FD – Fair Disclosure (Reg FD). Proponents of Reg FD argued that selective disclosure of information encourages analysts to provide biased recommendations in order to maintain good relations with the firm management in order to remain privy to first hand information. Thus, Reg FD was created to promote full and fair disclosure, such that any new material information released by companies to a select group e.g. analysts, must be made fully public.

and reported earnings in a dynamic information network. The findings are independent of the concerns on methodological issues in the previous literature.

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

The relationships between stock prices, earnings forecasts and reported earnings have been studied extensively by numerous researchers. Most of the literature cited in Section 1 focuses on the short run relationships between stock price reactions to reported earnings and analyst forecasts, although it is recognized that there are long run components in stock prices, earnings and their associated forecasts.

Our study builds on the premise of earlier work by Ou and Penman (1989) and Beaver, Lambert and Morse (1980) which show that the permanent component of prior earnings can provide explanatory power in predicting future earnings and stock prices. 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*).

Analysts earnings forecasts can be viewed as a sufficient summary statistic[6] that incorporate general market information, as well as the numbers in the financial statements of the firm, including past reported earnings, to predict the future earnings of the firm. Therefore, it is not unreasonable to conclude that there exists a linkage between past earnings, current analyst forecasts and the future reported earnings. Recent research also suggests that management try to influence analyst forecasts, for example, through the strategic release of profit warnings and management forecasts (Libby, Tan and Hunton, 2006; Soffer, Thiagarajan and Walther, 2000). Our paper launches off the preceding arguments to provide evidence on the mutual inter-dependence of the lead, lag or contemporaneous relationships between reported earnings and earnings forecasts of a firm.[7]

A major contribution of our paper is that it uses a lead-lag structure to model *both* short-run and long-run interactions between reported earnings and earnings forecasts, thereby accounting for a permanent component as well as medium and short-run interactions. This approach not only presents a formal framework to document the interactions between analyst forecasts and reported earnings, independent of stock price reactions, it also provides an alternative perspective to the findings reported in previous work such as Ali, Klein and Rosenfeld (1992, p.197) which conclude that "analysts

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[6] The concept of "sufficiency" that we have in mind here is analogous to the normal statistical definition of a "sufficient" statistic – that is, a sufficient statistic (analysts forecast) for θ (the reported earnings) captures all the relevant information about θ that is in the data (environment).

[7] There 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). However to keep our research design manageable, we do not attempt to disentangle the permanent and transitory components.

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 valuable alternative source of information which can be thought of as a type of 'amalgam' filter of all such sources is the analyst reports. Many researchers suggest that analyst reports are the 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. Does this mean that earnings reports can be "replaced" by analyst reports?

Francis, Schipper and Vincent (2002) directly examine analyst reports as the primary source of competing information and ask whether they reduce the usefulness of reported earnings, as measured by the market price reaction to the earnings announcement. In their main tests, they examine both mean and aggregate absolute abnormal return (AAR) for both analyst reports and earnings announcements related to a

particular financial year.[8] They find 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 find 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 might be consistent with analyst reports being a complementary information source rather than a substitutionary information source to earnings announcements.[9]

Asquith, Mikhail and Au (2005) examine analysts' reports and the market reaction to the release of the reports. They find that analysts provide new information and interpret previously released information. In addition, they also find that the market reacts to all of the elements of the report, namely, earnings forecast revisions, recommendation revisions, and price target revisions. They also conclude 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 stock price impact of analyst reports, controlling for endogeneity among factors that may contribute to the information environment. They find that analysts' reports are informative, that the information

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[8]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."

[9]Cheng (2005) concludes, on research in a related area, that while analysts do use information contained in financial reports, they 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.

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 recognize and attempt to incorporate the interaction of public and private information. They identify institutions such as financial analysts and large stockholders (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 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 reinforce the acquisition of private information by these institutions.

In addition, the Kim and Verrecchia 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 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 firm) 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 to 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 might show that analysts are not directly competing with the firm's disclosures and is "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.

For many of the above-mentioned papers (and for this literature in general), a major unresolved issue is whether the same conclusions are valid if stock market reactions are not used as the basis for assessing the link between analyst reports and earnings announcements. Accordingly, we provide an alternative empirical approach that delivers such evidence – with a special focus on the issue of whether analyst reports are substitutes, complements or simply repeats of reported earnings.

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.

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 hypothesize 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 either 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 earnings) 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 reports Granger "cause" analyst forecasts)*

The first hypothesis is tested against the null that earnings forecasts do not Granger cause reported earnings, while the second is tested against the null that reported earnings do not Granger cause earnings forecasts. For a given firm, if the null is rejected in both cases, then we can conclude that there is bi-directional causality, whereas if we fail to reject the null in both cases then there is no evidence of causality in either direction. After

conducting formal tests against H1 and H2, we can use the results to classify each firm into one of four categories, involving bi-directional causality, uni-directional causality (two cases) and no causality. These scenarios are summarized in Table 1.

[Table 1 about here]

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* provide 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 additional 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 paper is that we assess information flows between earnings and forecasts, using a careful adaptation of a widely acclaimed time series approach that does not rely on any measurement of stock market consequences. In 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

There are alternative/competing sources of public information capable of providing insights into the direction and, to a certain extent, the magnitude of current year earnings. These sources can be characterized into three broad categories: (a) firm specific; (b) industry specific;[10, 11] and (c) country or economy wide. Our direct focus in this paper will be on firm specific information and analyst forecasts specific to the firm. Firm specific information includes prior period earnings of the firm and voluntary management earnings forecasts or guidance.[12]

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) and the date (s_t) on which the earnings report was issued. Analysts' forecasts of earnings per share ($f_{jt\tau}$, for analysts $j = 1,2,…,J_t$), and the date τ 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

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[10] 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.

[11] Foster (1981), Baginski (1987) and Clinch and Sinclair (1987) show that there are intra-industry information transfers. Firms that report earlier, provide general information about the earnings of firms 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 stock price is generally associated with a positive (negative) change in the stock prices of other firms in the same industry." (Clinch and Sinclair, 1987, p. 90).

[12] Baginski (1987), in his examination of a firm's management forecasts of earnings, shows that they affect the stock 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 paper, we do not seek to directly incorporate these effects but assume that they are information components fully captured by and incorporated into analyst forecasts.

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 the 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.[13] Figure 1 provides a pictorial representation of the three different types of forecasts.

[Figure 1 about here]

Figure 2 shows the distribution of earnings forecasts for Marsh and McClennan during the first quarter of 1985, as an illustrative example of a typical situation in our

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[13] 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). Other things being equal, Type 3 forecasts are 'information rich' as they occur in a time period in which management are most active in providing guidance to the analysts since the quarter is over and the management will have proprietary information about quarterly performance. Management may resort to preannouncements to manage the analysts so as to avoid any possible earnings disappointments (Matsumoto, 2002).

sample.[14] In this case there were a total of nine forecasts. Two Type 1 forecasts were made before the release (on January 31 1985) of the report for the fourth quarter 1984 earnings, five Type 2 forecasts were made between the release of the fourth quarter report and the end of the first quarter of 1985, two Type 3 forecasts (both of same value) were made between the end of the first quarter 1985 and the release of the corresponding report on April 30 1985, and one Type 4 forecast was made after the release of the report.[15]

[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 have the benefit of the information contained in the 1984:4 earnings that were announced on January 31 1985. *Type 2* forecasts (in the section labelled 'T2') incorporate the information in the announced 1984:4 earnings, 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.

Of the 19,983 firms in our original sample, there were 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. Over the period of analysis, our sample firms have market capitalization ranging from US$15 million to US$596 billion dollars (Microsoft Corp). The median (average) market capitalization of the sample was US$2.9 billion (US$12.1 billion). The sample covers 35 two-digit SIC industries with no

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[14]Marsh and McClennan is a professional services firm providing consulting advice in the areas of risk, strategy and human capital. The firm belongs to the GICS financial services sector.

[15] Type 4 forecasts 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.

more than ten percent of the sample drawn from the two main industries, Electronic and other electrical equipment and components, except computer equipment (SIC 36) and Electric, gas, and sanitary services (SIC 49).

Summary details of the reported earnings and associated forecasts for these firms are displayed in Table 2. Our final sample contains 9,078 observations and 126,202 forecasts. Most (80.1%) of these forecasts are of the *Type 2* variety – they are issued after the last earnings announcement, but before the end of the current reporting quarter. An additional 17.4% are of the *Type 3* variety – they are forecasts issued after the quarter has ended but before the earnings report is actually made public.

[Table 2 about here]

3.2 Are analyst forecasts unbiased?

The lower half of Table 2 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. This switch from analysts' optimism to pessimism over time is not surprising. Richardson, Teoh and Wysocki (2004, p. 885) called this the "earnings-guidance game" where 'analysts first issue optimistic earnings forecasts and then "walk down" their estimates to a level that firms can beat at the official earnings announcement'. Initially, analysts are keen to develop a positive relationship with management and thus early earnings forecasts tend to be optimistic. It is

likely that as management takes a more active role to manage the analysts' expectations just before the earnings announcement through preannouncements, we would expect more analysts' pessimism (Lennox and Park, 2006; Richarson, Teoh and Wysocki; 2004; Matsumoto, 2002).

The bottom portion of Table 2 shows the correlations between the absolute value of the forecast errors and the time (in 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. This finding is consistent with the error convergence property of analyst forecasts over time and one of the major explanations for this convergence property is the enlargement of the information set as the firm approaches its earnings announcement date.

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

$$\hat{e}_t \; = \; -0.0008 \; + \; 0.9851\, f_t \quad with \quad R^2 = 0.864 \quad and \quad N = 126202.$$
$$\quad\quad (-0.217) \quad\quad (100.6)$$

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.[16] 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} and d_{3t}) produces the following

outcome:

$$\hat{e}_t = -0.011d_{1t} \quad -0.002d_{2t} \quad -0.006d_{3t} \quad + 0.896 \; d_{1t}f_t \quad + 0.981 \; d_{21t}f_t \quad + 1.011 \; d_{3t}f_{t,}$$
$$\quad (-0.99) \qquad (-0.05) \qquad (-0.12) \qquad (21.84) \qquad (92.34) \qquad (97.74)$$

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.[17]

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 characterize the relationship between the earnings forecasts and the reported

earnings. In particular we are interested in whether there is information in the earnings

forecasts (reported earnings) that is useful for predicting reported earnings (earnings

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[16] We address the issue of how the presence of unit roots might affect inference when we present time series regressions of earnings on forecasts.

[17] Details are not reported to conserve space.

forecasts), and whether the earnings forecasts (reported earnings) contain information that is not contained in past reported earnings (earnings forecasts). A time series technique often used to address issues such as these is the Granger causality test. However, this test is 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 debate regarding which combinations are optimal, it is widely recognized 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 $f_{jt\tau}$ is a *Type 2* forecast and zero otherwise, we focus on f_{2t} defined below, as our primary forecast variable:

$$f_{2t} = \frac{1}{\sum d_{2t}} \sum_{j=1}^{J_t} \left(f_{jt\tau} \times d_{2t} \right) \tag{1}$$

This forecast metric takes the arithmetic average of *Type 2* forecasts, across analysts for a given firm, in a specific quarter. *Type 2* forecasts are "standard" forecasts, in the sense

that while they might incorporate past earnings information, they do not incorporate any

information that becomes available after the end of the reporting period.

Alternatively, we also calculate:

$$f_{12t} = \frac{1}{\sum d_{12t}} \sum_{j=1}^{J_t} \left(f_{jt\tau} \times d_{12t} \right) \tag{2}$$

$$f_{23t} = \frac{1}{\sum d_{23t}} \sum_{j=1}^{J_t} \left(f_{jt\tau} \times d_{23t} \right) \tag{3}$$

$$f_{123t} = \frac{1}{\sum d_{123t}} \sum_{j=1}^{J_t} \left(f_{jt\tau} \times d_{123t} \right) \tag{4}$$

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 firm, in a specific quarter.[18]

Figure 3 compares the three forecast combinations for an illustrative sample firm,

Eli Lilly.[19] 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 firm. 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 corporate earnings

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[18] 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.

[19] Eli Lilly, established in the 1870s, is a leading producer of prescription drugs. Accordingly, it belongs to the Healthcare GICS sector, and is classified in the pharmaceuticals sub-industry.

impact of the 1987 stock market crash. Such 'failures' were observed for several (but not all) firms for this quarter, and similarly large forecast errors were observed once or twice at other times across most of the sample.

[Figures 3 and 4 about here]

Table 3 reports the time series properties of earnings and forecast combinations. It shows that for most of the 122 firms in our sample, there is a quarterly seasonality in the data series and evidence of a 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 de-trended, the de-trended data fails to be mean reverting, so that the series "wanders" rather than returns to trend. The variance is also non-constant, growing with the sample size. These properties can imply that standard t and F tests statistics do not have the usual t and F distributions, so that care is needed when attempting to draw inferences based on the usual types 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 3 about here]

Table 4 provides some preliminary analysis of the relationship between reported earnings and earnings forecast combinations. The usual tests of "good forecasting" are provided in column 3 and 4, although it needs to be noted that the time series behavior 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 $e_t = f_t +$ a zero

mean prediction error, for about thirty out of the 122 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.[20] 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.[21]

[Table 4 about here]

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:

$$x_t = c_x + \sum_{j=1}^{j=p} \alpha_j x_{t-j} + \sum_{j=1}^{j=p} \beta_j y_{t-j} + \varepsilon_{xt} \tag{5}$$

$$y_t = c_y + \sum_{j=1}^{j=p} \gamma_j x_{t-j} + \sum_{j=1}^{j=p} \delta_j y_{t-j} + \varepsilon_{xt}$$

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[20] Campbell and Shiller (1988) discuss this issue in the context of forecasting dividends. This is also consistent with the notion that analysts have the ability to forecast the permanent component of earnings of a firm relatively accurately.

[21] Formally, the tests are performed using the augmented Dickey-Fuller (1979) approach. In this case, the rejection of a unit root supports cointegration and a long run relationship between earnings and forecasts.

and a test that X_t does not Granger cause Y_t (i.e. $H_0 : X_t \nrightarrow Y_t$) 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: $X_t \nrightarrow Y_t$ does not mean that X_t might cause Y_t in any physical sense; rather, he stresses the forecasting implication that the history of X_t (i.e. $X_t^H = \{x_{t-1}, x_{t-2}, \dots x_t\}$ must contain information that is not contained in $Y_t^H = \{y_{t-1}, y_{t-2}, \dots y_t\}$, and that this additional information is useful for predicting y_t. Similarly, a rejection of H_0: $Y_t \nrightarrow X_t$ 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:

$$\Delta x_t = c_x + \lambda_x \left(x_{t-1} - \pi_x y_{t-1} \right) + \sum_{j=1}^{j=p-1} \alpha_j^* \Delta x_{t-j} + \sum_{j=1}^{j=p-1} \beta_j^* \Delta y_{t-j} + \varepsilon_{xt} \tag{6}$$

$$\Delta y_t = c_y + \lambda_y \left(y_{t-1} - \pi_y x_{t-1} \right) + \sum_{j=1}^{j=p-1} \gamma_j^* \Delta x_{t-j} + \sum_{j=1}^{j=p-1} \delta_j^* \Delta y_{y-j} + \varepsilon_{yt}$$

where $\lambda_x = \sum\alpha_j - 1$, $\pi_x = \sum\beta_j/\lambda_x$, and the α_j^*, β_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), π_x measures the long-run impact of y_t on x_t, and π_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 $x_t = \pi_x y_t$ and at least one of λ_x or λ_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 $x_{t-1} - \pi_x y_{t-1}$ is non-stationary. In this case OLS will force $\hat{\lambda}_x$ and $\hat{\lambda}_y$ to zero so as to minimize 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 $H_0:$ all $\beta_j^* = 0$, and the overall test is a joint test of both of these hypotheses. The mirror images of these tests apply for the converse case of the null that x_t does not Granger cause y_t.

4.2 Modified Granger causality tests

Our time series for reported earnings and their forecasts do not fully 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 $\{f_t, f_{t-1}, f_{t-2}, ...f_1\}$ contains information

about e_t, over and above the information in $\{e_{t-1},\ e_{t-2},\ ...e_1\}$, whereas a standard Granger

causality analysis asks whether $\{\ f_{t-1},\ f_{t-2},\ ...f_1\}$ contains information about e_t, over and

above the information in $\{e_{t-1},\ e_{t-2},\ ...e_1\}$. 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 $\{e_{t-1},\ e_{t-2},\ ...e_1\}$

contributes to forecasts f_t, given that $\{f_{t-1}, f_{t-2},\ ...f_1\}$ is known. This leads us to consider the

system specified by:

$$e_t = c_e + \sum_{j=1}^{j=p}\alpha_j e_{t-j} + \sum_{j=0}^{j=p-1}\beta_j f_{t-j} +\varepsilon_{et} \tag{7}$$

$$f_t = c_f + \sum_{j=1}^{j=p}\gamma_j e_{t-j} +\sum_{j=1}^{j=p}\delta_j f_{t-j} +\varepsilon_{ft}$$

and its error correction parameterization given by

$$\Delta e_t = c_x + \lambda_e\left(e_{t-1} - \pi_x f_{t-1}\right)+ \sum_{j=1}^{j=p-1}\alpha_j^*\Delta e_{t-j} + \sum_{j=0}^{j=p-2}\beta_j^*\Delta f_{t-j} +\varepsilon_{et} \tag{8}$$

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

where we have normalized the error correction terms on e_t (and rescaled λ_f accordingly).

Tests of whether earnings forecasts lead reported earnings in the long run are based on λ_e,

tests of whether forecasts lead earnings in the short run are based on the β_j^*, and overall

tests of whether forecasts lead earnings are joint tests on λ_e and β_j^*. Similarly, tests of

whether past reported earnings provide information about current forecasts that is not

contained in past forecasts, are tests relating to λ_f^* and/or γ_j^*.

We call our tests Granger causality tests, but emphasize 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 lag so that we can use the Toda and Yamamoto (1995) results and have confidence in our inferences. We also include quarterly dummies in (7) and (8) to account for the seasonality reported in Table 3, 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. $z_t = e_t - \pi_x f_t$), 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 5 presents summary information relating to our estimates of the equations in (7) for each of the 122 firms. Reported regressions are based on: (a) *Type 2* forecasts (i.e. we set $f_t = f2_t$); (b) combined *Type 1 & 2* forecasts in which $f_t = f12_t$; (c) combined *Type 2 & 3* forecasts in which $f_t = f23_t$; and (d) all types of forecasts in which $f_t = f123_t$. All test

statistics are based on Toda and Yamamoto's approach so that inference is valid despite possible non-stationarity, and they are also corrected for residual heteroskedasticity and serial correlation.

The first thing to note is that the estimated equations fit the data very well, with the average R^2 measures being around 90%. In columns 3 and 5 we present the results of "Granger causality" tests based on the β and γ coefficients, to provide an indication of the causality structure in the data. The reported counts suggest that past forecasts are useful for predicting current earnings in all but seventeen (three) firms for *Type 2* forecasts (all types of forecasts). Here, the tests are conditioned on past earnings, so that the Granger causality indicates that past forecasts are providing additional information on future earnings to that contained in past earnings. There are not pronounced differences between the results found for different types of forecasts, but it seems that the later the forecasts, the more likely they are to be useful for predicting earnings. Column 5 indicates that analysts often incorporate information from past earnings into their forecasts, even after using information contained in past forecasts. Indeed, for Type 2 (*Type 1 & 2*) forecasts, there are only twenty nine (twenty eight) cases in which analysts do not seem to be using information on past earnings when forming their forecasts. By comparison, for all types of forecasts, the number of cases in which analysts do not seem to be using information on past earnings has grown to thirty five.

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 firms. This is particularly

noteworthy given that the previous accounting literature has found or assumed much shorter persistence in earnings, but it is quite consistent with Ou and Penmen's (1989) notion of a permanent component in earnings. Indeed, this finding of a long-lived persistence in earnings/forecasts is a major contribution of our paper as most studies only provide an understanding of the lead-lag relationship between reported earnings and stock prices (Ou and Penman; 1989 and Beaver, Lambert and Morse; 1980).[22]

[Table 5 about here]

Tables 6 and 7 present details relating to estimated versions of the re-parameterized 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 6 and 7 are also similar to those in Table 5. For the first differences in reported earnings equations in Table 6, 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.[23] The estimated λ_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. The error correction models that impose unbiased forecasts lead to slightly stronger results, finding more evidence of causality than in the unrestricted case.

[Tables 6 and 7 about here]

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[22] See Nichols and Wahlen (2004) for a review of the accounting research on the relationship between earnings numbers and stock returns.

[23] We find similar results for the case in which there is imposed error correction term.

For the quarterly changes in earnings forecasts shown in Table 7, 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. As was the case for Table 6, 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 (Table 7, columns (3) and (7)). For cases when the estimated λ_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 (Table 7, columns (7) and (8)). This suggests that analysts often find recent past earnings reports useful when forming their forecasts, but they are less likely to find the entire history of past earnings useful when forming these forecasts. This is a central finding in our paper as it is the first time substantial empirical evidence is provided to support this intuitive conclusion in a time series framework.

Tables 8 and 9 provide an overview of the results of the tests. Using the framework outlined in Table 1 (Categories C1 to C4), generally, these tables show that there is bi-directional causality (C1) for about 75% of firms (using both the estimated and implied

error correction terms). Most of this causality is of the short-run variety (Table 8, Panel D: 58.2%; Table 9, Panel D: 60.7%), rather than long-run (Table 8, Panel D: 18.0%; Table 9, Panel D: 21.3%). For short-term and overall Granger causality, there are only very few cases where neither earnings nor forecasts influence each other. The tables present compelling evidence that forecasts can predict earnings, but they also show that earnings provide information that is utilized in subsequent forecasts. This suggests that forecasts complement, rather than substitute for earnings reports.

[Tables 8 and 9 about here]

Two important observations are gleaned from Tables 8 and 9. First, cases of bi-directional and uni-directional Granger causality are much more prevalent in the short-run as compared to the long-run. Second, it is heartening to observe that earnings forecasts Granger cause reported earnings in considerably more cases than reported earnings Granger cause forecast earnings. This clearly shows the important role played by earnings forecasts in capturing the information content of reported earnings and, hence, the important role played by analysts in providing information to the market about the reported earnings of firms.

6. Conclusion

We conduct suitably adapted Granger causality tests to study information flows between analyst earnings forecasts and reported earnings. This time-series methodology complements the standard cross-sectional techniques that are often based on stock market reactions to the arrival of news, by enabling analysis on the lead-lag structure of the information content in forecasts and reports. We reconfirm previous evidence of a

positive bias in forecasts, but also find that this evidence becomes weaker as the forecast horizon becomes shorter. Further, we find that the lag structure in information flows is longer (up to twelve quarters) than has been assumed in previous literature.

Our Granger causality tests find that analysts' earnings forecasts Granger-cause reported earnings in the short run for nearly all firms. Furthermore, analysts earnings forecasts Granger-cause reported earnings in the long run for about half of all firms. This provides time series evidence that forecasts are useful for predicting future earnings despite forecast bias. In both cases, the Granger causality implies that the forecasts contain information over and above that which is contained in past earnings alone.

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. Taken together, our test results demonstrate that there is pervasive bi-directional causality, even though we document stronger forecast to reporting earnings Granger causality than causality in the reverse direction. However, this latter type of causality is particularly interesting, because it implies that future forecasts are not simply based on previous forecasts; they rely on additional information contained in earnings reports as well. Thus we conclude that forecasts do not (fully) substitute for the reported earnings figures, but rather, they complement the information contained in reported earnings.

Our time series approach offers a new perspective on how analyst forecasts and earnings reports contribute to the information set on a firm's performance, because it explicitly accounts for the timing of information events. Further, our approach allows for (non constant) firm specific differences in behavior, since we have *not* averaged across different firms (as in standard cross-sectional analysis, or in standard analyses of panels).

Our summary results show that the causality results differ across firms especially in the long-run, and especially when one considers the impact of past earnings reports on forecasts. Our future research will focus on the determination of firm and analyst characteristics that have an influence on whether earnings do (or do not) Granger cause forecasts (and whether forecasts do, or do not Granger cause earnings).

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Table 1: Categories of Granger Causality between Reported Earnings and Earnings Forecasts

	Earnings Forecasts (*f*) Granger Cause Reported Earnings (*e*)	Earnings Forecasts (*f*) do not Granger Cause Reported Earnings (*e*)
Reported Earnings (*e*) Granger Cause Earnings Forecasts (*f*)	*C1:* Bi-directional causality $e \overset{GC}{\underset{\leftarrow}{\rightarrow}} f$	*C2:* Uni-directional causality $e \overset{GC}{\rightarrow} f$
Reported Earnings (*e*) do not Granger Cause Earnings Forecasts (*f*)	*C3:* Uni-directional causality $f \overset{GC}{\rightarrow} e$	*C4:* No causality at all

Table 2: Properties of Analyst Earnings Forecasts

Properties	All Forecasts	Type of Earnings Forecast		
		Type 1	*Type 2*	*Type 3*
Total Count	126,202	3,087	101,112	22,003
mean forecast error ($f-e$)	0.0068***	0.0460***	0.0080***	-0.0041*
HAC. standard error ($f-e$)	0.0019	0.0091	0.0019	0.0025
corr ($|f-e|$, ($s-\tau$))	0.0358***	-0.0022	0.0253***	0.0832***
HAC. standard error (corr)	0.0028	0.0180	0.0031	0.0067

Notes:

The symbols *** and * signify statistically significant at the 1% and 10% levels respectively. The quantity ($s-\tau$) measures the time between when the earnings forecast (f) was made and when the reported earnings (e) was issued. HAC standard errors are corrected for heteroskedasticity and autocorrelation. Forecasts (f) 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 'target' quarter but before the reporting date of the earnings.

Table 3: Properties of Time series for Reported Earnings and Earnings Forecast Combinations

Earnings / Forecast Type (1)	Ave R^2 (2)	No. of Outliers		Number of Rejections (at 5% level)		
		< 6se (3)	> 6se (4)	H_0: $\alpha_0 = 0$ (5)	H_0: $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4$ (6)	H_0: unit root (7)
Earnings	0.5156	27	10	92	82	22
Forecasts						
Type 2	0.4993	40	2	85	81	33
Type 1 & Type 2	0.5322	17	4	86	82	26
Type 2 & Type 3	0.5168	27	1	89	82	30
All Forecasts	0.5593	6	2	91	84	21

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. See Table 2 for a description of the forecast types.

Table 4: Relationship between Reported Earnings and Earnings Forecast Combinations

| Forecast Type | Ave R^2 | Number of Rejections | | H_0: unit root | |
| | | H_0: $\beta_1 = 1$ | H_0: $\beta_0 = 0$ & $\beta_1 = 1$ | $e_t - \beta_1 f_t$ | $e_t - f_t$ |
(1)	(2)	(3)	(4)	(5)	(6)
Type 2	0.7118	29	31	87	100
Type 1 & Type 2	0.7607	26	31	91	98
Type 2 & Type 3	0.7714	28	30	94	100
All Types	0.8346	23	29	98	98

Notes:

The 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. See Table 2 for a description of the forecast types.

Table 5: Predictability of Reported Earnings and Earnings Forecasts

| Forecast Type | Equation for Earnings | | Equation for Forecasts | |
| | Ave R^2 | Rejections of H_0: f does not Granger Cause e (5 % level) | Ave R^2 | Rejections of H_0: e does not Granger Cause f (5 % level) |
(1)	(2)	(3)	(4)	(5)
Type 2	0.9132	105	0.8883	93
Type 1 & Type 2	0.9118	108	0.9045	94
Type 2 & Type 3	0.9384	116	0.9067	90
All Types	0.9391	119	0.9300	87

Notes:

The 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 $\beta_j = 0$ (except for the augmented lag) and H_0: e does not Granger Cause f implies that all $\gamma_j = 0$ (except for the augmented lag). All test statistics have been calculated using HAC consistent covariances. See Table 2 for a description of the forecast types.

Table 6: Predictability of First Differences in Reported Earnings (*e*) – Do Earnings Forecasts (*f*) Granger Cause Reported Earnings (*e*)?

| Forecast Type (1) | Estimated Error Correction Term | | | | Imposed Error Correction Term | | | |
| | Ave R^2 (2) | Number of Rejections (5 % level) | | | Ave R^2 (6) | Number of Rejections (5 % level) | | |
		No LRC (3)	No SRC (4)	No GC (5)		No LRC (7)	No SRC (8)	No GC (9)
Type 2	0.8294	58	108	112	0.8327	64	109	109
Type 1 & Type 2	0.8388	61	113	116	0.8406	64	113	114
Type 2 & Type 3	0.8669	65	115	116	0.8707	70	116	116
All Types	0.8834	69	120	120	0.8857	70	120	120

Notes:

The 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, but it includes quarterly dummies as well. For the columns labelled "Estimated Error Correction Term" we replace the (e_{t-1} – $\pi_x f_{t-1}$) term by z^1_{t-1}, and for the columns labelled "Imposed Error Correction Term" we replace the (e_{t-1} – $\pi_x f_{t-1}$) 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 $\beta^*_j = 0$. All test statistics have been calculated using HAC consistent covariances. See Table 2 for a description of the forecast types.

Table 7: Predictability of First Differences in Earnings Forecasts – Do Reported Earnings (*e*) Granger Cause Earnings Forecasts (*f*)?

| Forecast Type (1) | Estimated Error Correction Term | | | | Imposed Error Correction Term | | | |
| | Ave R^2 (2) | Number of Rejections (5% level) | | | Ave R^2 (6) | Number of Rejections (5% level) | | |
		No LRC (3)	No SRC (4)	No GC (5)		No LRC (7)	No SRC (8)	No GC (9)
Type 2	0.7335	37	76	93	0.7476	54	72	101
Type 1 & Type 2	0.7442	39	74	91	0.7507	48	75	96
Type 2 & Type 3	0.7442	38	72	92	0.7474	41	70	95
All Types	0.7522	40	72	93	0.7486	40	75	93

Notes:

The information reported in this table relate to a sample of 122 firms. Lag lengths *p* were chosen using AIC for each bivariate system. The forecast equation is the second of the two in equation (8) in the text, but it includes quarterly dummies as well. For the columns labelled "Estimated Error Correction Term" we replace the (e_{t-1} – $\pi_x f_{t-1}$) term by z^1_{t-1}, and for the columns labelled "Imposed Error Correction Term" we replace the (e_{t-1} – $\pi_x f_{t-1}$) 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 $\gamma^*_j = 0$. All test statistics have been calculated using HAC consistent covariances. See Table 2 for a description of the forecast types.

Table 8: Joint Outcomes of Granger Causality Testing for the case in which an Estimated Error Co

	Short-run Granger Causality (SRC)		Long-run Granger Causality (LRC)		O
	f "causes" *e*	*f* does not "cause" *e*	*f* "causes" *e*	*f* does not "cause" *e*	*f* "
Panel A: Type 2 Forecasts					
e "causes" *f*	71 (58.2%)	5 (4.1%)	16 (13.1%)	21 (17.2%)	85
e does not "cause" *f*	37 (30.3%)	9 (7.4%)	42 (34.4%)	43 (35.2%)	27
Panel B: Type 1 & Type 2 Forecasts					
e "causes" *f*	72 (59.0%)	2 (1.6%)	19 (15.6%)	20 (16.4%)	87
e does not "cause" *f*	41 (33.6%)	7 (5.7%)	42 (34.4%)	41 (33.6%)	29
Panel C: Type 2 & Type 3 Forecasts					
e "causes" *f*	70 (57.4%)	2 (1.6%)	19 (15.6%)	19 (15.6%)	87
e does not "cause" *f*	45 (36.9%)	5 (4.1%)	46 (37.7%)	38 (31.1%)	29
Panel D: All type Forecasts					
e "causes" *f*	71 (58.2%)	1 (0.8%)	22 (18.0%)	18 (14.8%)	92
e does not "cause" *f*	49 (40.2%)	1 (0.8%)	47 (38.5%)	35 (28.7%)	28

Notes:

After conducting formal tests against H1 and H2, we use the results from Tables 6 and 7 to classify each firm into one of four
Table 1. The information reported in this table relate to a sample of 122 firms, for the case in which an estimated error correcti
forecasts are separated into three types according to their timing relative to the quarter to which they relate. *Type 1* forecasts oc
reported earnings for the previous quarter; *Type 2* forecasts occur during the quarter, but post *Type 1* forecasts; and *Type 3* for
of the 'target' quarter but before the reporting date of the earnings.

Table 9: Joint Outcomes of Granger Causality Testing for the case in which an Imposed Error Corr

|	Short-run Granger Causality (SRC)		Long-run Granger Causality (LRC)		O
	f "causes" *e*	*f* does not "cause" *e*	*f* "causes" *e*	*f* does not "cause" *e*	*f* "c
Panel A: Type 2 Forecasts					
e "causes" *f*	68 (55.7%)	4 (3.3%)	28 (23.0%)	26 (21.3%)	88
e does not "cause" *f*	41 (33.6%)	9 (7.4%)	36 (29.5%)	32 (26.2%)	21
Panel B: Type 1 & Type 2 Forecasts					
e "causes" *f*	73 (59.8%)	2 (1.6%)	24 (19.7%)	24 (19.7%)	89
e does not "cause" *f*	40 (32.8%)	7 (5.7%)	40 (32.8%)	34 (27.9%)	25
Panel C: Type 2 & Type 3 Forecasts					
e "causes" *f*	68 (55.7%)	2 (1.6%)	22 (18.0%)	19 (15.6%)	89
e does not "cause" *f*	48 (39.3%)	4 (3.3%)	48 (39.3%)	33 (27.0%)	27
Panel D: All type Forecasts					
e "causes" *f*	74 (60.7%)	1 (0.8%)	26 (21.3%)	14 (11.5%)	92
e does not "cause" *f*	46 (37.7%)	1 (0.8%)	44 (36.1%)	38 (31.1%)	28

Notes:

After conducting formal tests against H1 and H2, we use the results from Tables 6 and 7 to classify each firm into one of four
Table 1. The information reported in this table relate to a sample of 122 firms, for the case in which an imposed error correcti
forecasts are separated into three types according to their timing relative to the quarter to which they relate. *Type 1* forecasts o
reported earnings for the previous quarter; *Type 2* forecasts occur during the quarter, but post *Type 1* forecasts; and *Type 3* for
of the 'target' quarter but before the reporting date of the earnings.

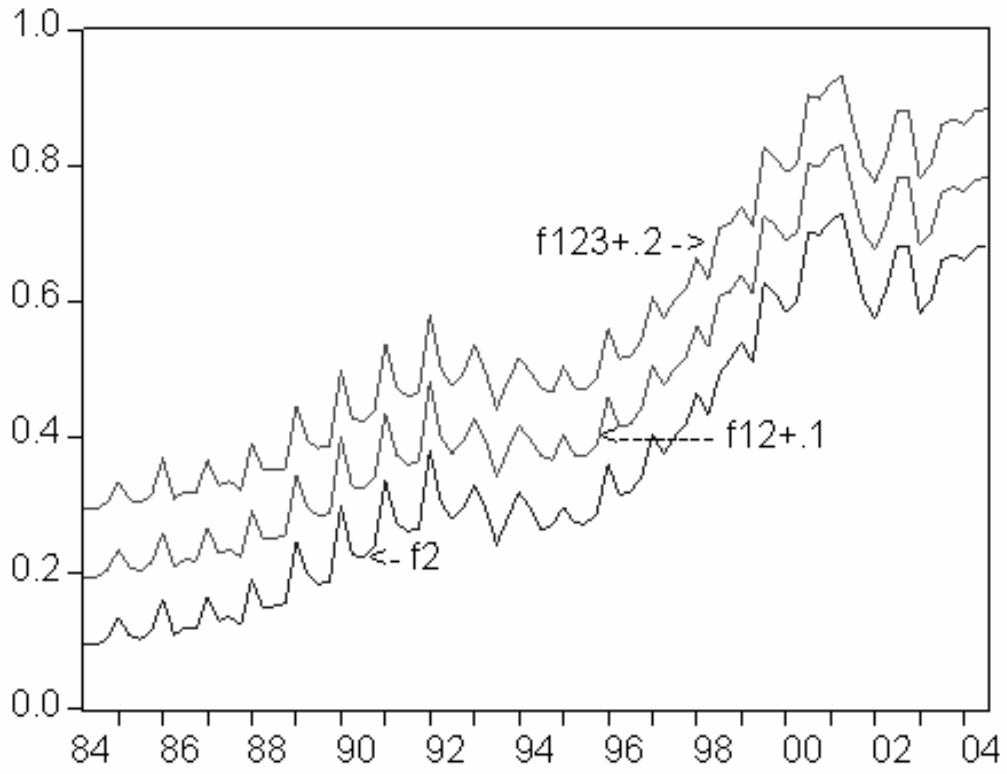**Figure 1: Characterizing Different Types of Analyst Earnings Forecast**
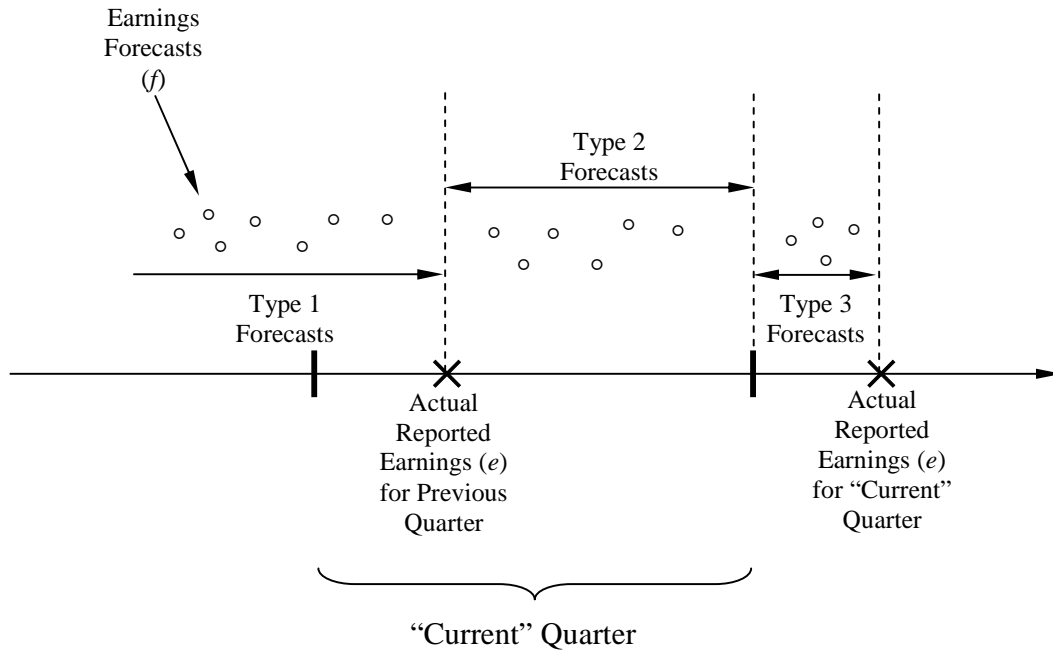
Figure 2: Forecasts for 1985 First Quarter Earnings
Marsh and McClennan

(○ indicates the earnings forecasts (*f*), × indicates the reported earnings (*e*))
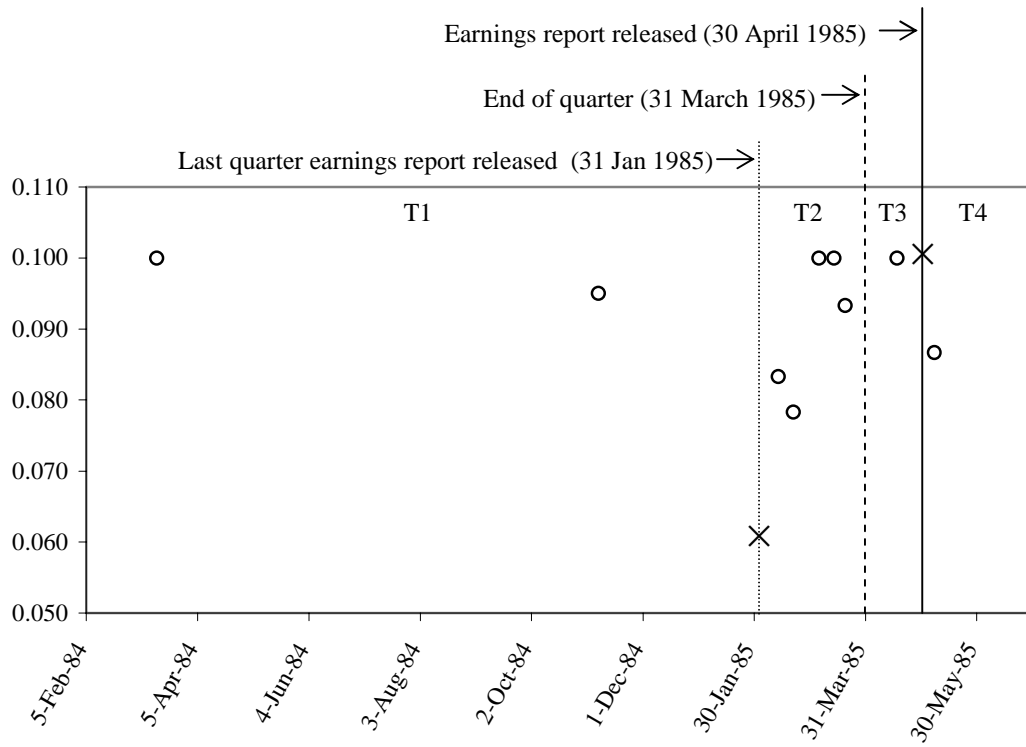
Figure 3: Comparison of Forecast Combinations
(Eli Lilly Company)

Figure 4: Comparison of Earnings and f2 Combination Forecasts
(Eli Lilly Company)