Lead indicator models and UK analysts' earnings forecasts

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Abstract—This study examines the predictive ability of models which adjust random walk forecasts of corporate earnings, to incorporate past changes in economic lead indicators. The results suggest that changes in the *broad* money supply measure M4 contain predictive ability, beyond equivalent changes in other lead indicators or an individual firm's earnings. When forecasts from the broad-money model are compared with forecasts generated by financial analysts a size effect is evident: the superiority of analysts' forecasts is apparent much earlier for large firms than for small firms. This result is consistent with studies suggesting a size-related differential in the collection and dissemination of information by market participants.

1. Introduction

Interviews with analysts (e.g. Arnold and Moizer, 1984: 197) reveal that economy-wide data is often utilised in the assessment of general corporate prospects and in the prediction of earnings numbers. However, researchers' attempts to model the series for corporate earnings are usually *univariate* in nature, ignoring the potential for predictive gains to *macroeconomic* data.

The issue can be summarised as follows. The most simple time series model—the random walk—is low cost from the view point of researchers, and has empirical justification. Early studies of the time series for annual corporate earnings in both the UK (Little, 1962) and the US (Linter and Glauber, 1967) provide evidence consistent with a random walk process. Later US studies indicate that the series for quarterly earnings may be described by various forms of Box-Jenkins models (e.g. Foster, 1977; O'Brien, 1988), but in many countries, including the UK, quarterly earnings numbers are not usually disclosed.

Box-Jenkins models have not proved effective where only annual earnings data are available (see Watts and Leftwich, 1977: 269). More recently, the developing work on non-linear models (e.g. neural networks and chaos) has offered researchers additional tools for forecasting purposes. However, the large amounts of data needed for such procedures are typically not available for UK earnings series. Although some work is developing in this area for US earnings series (e.g. Callan et al., 1996), some academics recommend caution in the use of such non-linear models where the number of observations is limited:

> 'Recent applications in economic and sales forecasting have sometimes tried to "get away with" as few as 100 observations, and this seems generally unwise.' (Chatfield, 1996: 209).

Because of data limitations, possibly no significant gains may be found by further development of univariate models.

An alternative approach to earnings forecasting is to widen the information set beyond the series of realised earnings, to incorporate variables which may possess lead indicator properties for economic activity. The use of indicator variables is widespread in economic forecasting (see Zarnowitz, 1992) but has been used little in accounting research.

An exception is a US study by Chant (1980) that investigates how random walk forecasts of corporate earnings may be improved by adjusting for past changes in lead indicator variables. Equation (1) shows how Chant applies changes in economic lead indicators, to the most recent earnings number:

$$\hat{A}_{t+1} = A_t\,(1 + \Delta I_t) \qquad (1)$$

where $\hat{A}_{t+1}$ = forecast of annual earnings for firm's fiscal year t + 1

A_t = actual earnings for firm's fiscal year t

ΔI_t = proportionate change in level of lead indicator over the 12 month period of firm's fiscal year t

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Thus, changes in the indicator variable during fiscal year t are assumed to be reflected in corporate earnings for fiscal year $t+1$. Chant uses three lead indicators: seasonally unadjusted money supply M1; the S&P 425 industrial stock index, and bank loans. Chant also uses two time series models that utilise only past earnings numbers: an exponential smoothing model and an average growth model. However, only the money supply-adjusted model proves significantly superior to the random walk. It suggests that past changes in monetary aggregates contain additional predictive ability over changes in a firm's earnings series, as represented by the time series models.

Chant's study is entirely empirical in nature; it tests the accuracy of models with no theoretical analysis as to the links between the money supply and income. This emphasis on empirical analysis is reflected in a number of macroeconomic studies which investigate the lead indicator properties of monetary aggregates for nominal national income and prices (e.g. Crockett, 1970; Astley and Haldane, 1995). The usefulness of lead indicators to policy makers and forecasters is that they provide accurate signals about future changes in target variables. Indicators may contain information not available from other variables, or they may encapsulate information which is only obtainable through a costly analysis of a wide range of other variables (e.g. interest rates, exchange rates, etc.).

For forecasters, it is obviously more convenient to examine the signals from a single 'lead' variable, rather than having to analyse a wide range of other variables to obtain the same signals. Thus, even without a detailed structural analysis, such studies are useful for identifying variables which may allow improved forecasting of the target variable.

Several empirical questions arise from Chant's US study of corporate earnings. Firstly, can the results be generalised to other economies, in particular the UK? Secondly, could the models be improved by using different lead times for changes in lead indicators? Thirdly, are the results sensitive to the definition of money supply? Fourthly, how do such forecasts compare with those generated by market professionals? These issues are investigated in the present paper.

The remainder of the paper is divided into four sections. Section 2 describes the data and forecasting models employed, and defines the error metric for this study. Section 3 describes both the methods utilised for error analysis, and presents the test results. Section 4 presents additional evidence and discussion relating to issues which flow from the main analysis. Section 5 is the conclusion.

2. Data, models and error metric

2.1. The data

The proprietary firm-specific data used in this study were provided by a large London-based stockbroking firm. The dataset includes earnings forecasts and revisions for the 23 months prior to an announcement, realised pre-tax earnings numbers, year-ends and market values for 580 firm-year observations, with fiscal years covering the period 1986–89, inclusive. No restriction is placed on the month of the year-end and the resulting sample appears representative of firms listed on the London Stock Exchange.

However, firms with negative earnings numbers are eliminated. This procedure is partly used to avoid the problem of calculating percentages of negative numbers, but also because evidence from US studies (e.g. Ali, Klein and Rosenfeld, 1992) indicates that for firms announcing negative earnings numbers, the earnings series has differing time series properties—specifically, very strong mean reversion. For these reasons, it is decided to exclude firms with negative earnings. This restriction reduces the sample to 565 firm-year observations (list available on request).

The earnings forecasts in the dataset are generated by individual analysts within the stockbroking firm, and are precisely time-dated. This means that at each monthly horizon, above 23 months prior to an announcement, the most recently created forecast can be identified. Many studies of analysts' forecasts use publication dates to date forecasts, but this approach is criticised by O'Brien (1988: 59) because of the lag between creation and publication, which O'Brien finds to be around 34 days. Thus, the use of publication dates could lead to the identification of out-of-date forecasts, for a particular horizon, biasing results against analysts.

The use of individual analysts' forecasts here instead of consensus forecasts (e.g. IBES) could be criticised. It could be argued that individual analysts' forecasts are susceptible to idiosyncratic error, which may be 'averaged away' in consensus forecasts. However, O'Brien finds that for a given horizon, the most recently created individual forecast is superior to mean and median consensus forecasts, suggesting that timeliness is a more important factor than idiosyncratic error in determining accuracy. An explanation for this finding is that consensus forecasts sometimes include stale forecasts, which can adversely influence accuracy. The potential problem of stale forecasts is also mentioned by Stickel (1989: 291) as a potential explanation for the findings of those studies that suggest managers' forecasts are superior to those of analysts.

The following economic data were collected from Dun & Bradstreet's *Datastream* information service, for every month from January 1983, through December 1989: (a) bank and building society loans; (b) the *Financial Times* Stock Exchange 100 index; (c) the money supply M0; (d) the money supply M2, and (e) the money supply M4. For consistency with Chant, the money supply data are seasonally unadjusted. The money supply measure M0 consists of little more than notes and coins in circulation, plus banks' till money. The aggregates M2 and M4 also include a variety of deposit accounts. The measure M4 is currently considered the UK's main *broad-money* measure and M0 is the main *narrow-money* measure. These data comprise the candidate lead indicator variables examined in this study.

2.2. The models

The models used here build on those employed by Chant. The basic model is shown as equation (1). Here, the change in the lead indicator (ΔI_t) is calculated over the 12 months of fiscal year t, i.e. changes occurring over the fiscal year prior to the one being forecasted (year *t+1*). However, annual changes in lead indicators for lags of two and three years are also employed here, since lead indicators may lead economic activity by several years. Thus equation (2) to (4) are also employed here:

$$\hat{A}_{t+1} = A_t\,(1 + \Delta I_{t-1}) \qquad (2)$$

$$\hat{A}_{t+1} = A_t\,(1 + \Delta I_{t-2}) \qquad (3)$$

$$\hat{A}_{t+1} = A_t\,(1 + \Delta I_{GM}) \qquad (4)$$

where ΔI_{t-j} = proportionate change in level of lead indicator over the 12 month period of firm's fiscal year $t-j$

ΔI_{GM} = geometric mean of annual proportionate changes in the lead indicator such that

$$(1 + \Delta I_{GM}) = \sqrt[3]{(1 + \Delta I_t)\,(1 + \Delta I_{t-1})\,(1 + \Delta I_{t-2})}$$

and $\hat{A}_{t+1}$ and A_t are defined previously.

The final model, model (4), uses the geometric mean annual growth over a three-year period. This may be useful for lead indicators which are erratic in terms of year-on-year movements, but where the 'averaged' trend may be useful for predictive purposes.

2.3. The error metric

The error metric utilised here is the same as that used by Chant, and other studies of forecast accuracy (e.g. Basi, Carey and Twark, 1976; Brown and Rozeff, 1978; Patz, 1989); it is defined as

$$FE_{t+1} = \frac{|\hat{A}_{t+1} - A_{t+1}|}{A_{t+1}} \qquad (5)$$

Actual earnings is used as the deflator for the error metric in preference to a price based deflator like market value. For a study concerned solely with the measurement of accuracy, it would not be desirable to have differing error values for two firms which may have identical values for predicted and realised levels of earnings—and thus identical accuracy—but differing market values.[1] Some studies of forecast errors impose an upper bound on error values to guard against the influence of extreme observations; Chant (1980: 16) truncates all error values at 2.00 (i.e. 200%). For the purposes of comparability, this procedure is replicated here[2]; the impact of error truncation on the results of this study are not material. Repeating the analyses conducted here using unbounded errors generates almost idential results, and does not alter any of the main conclusions of this study.

3. Analysis and results

The analysis consists of two main elements. First, all lead indicator models are used to generate earnings forecasts for the 565 firm-year observations. Through statistical testing of forecast errors, the most accurate lead indicator model is identified. The second element of the analysis involves comparing forecasts from the most accurate lead indicator model, with forecasts generated by financial analysts.

3.1. A comparative analysis of the lead indicator models

The preliminary analysis of mean and median errors (omitted here for brevity) identifies the most accurate model form for each lead indicator. For the bank and building society loans model, the geometric mean growth adjustment (equation 4), is the most accurate model. This may be due to the 'smoothing' effect of using a three-year average growth value, because the series for bank loans is particularly volatile. For the FTSE-100 index model, it is equation 3 which is the most accurate. This latter result may be linked with the October crash of 1987. This study forecasts earnings numbers for 1986–89. Since equation 3 uses the longest lead time between indicator and earnings, the 1987 crash period would be omitted; even forecasts of earnings for 1989 year-ends would use the annual change in the FTSE-100, occurring up to the same year-end month in 1986.

With a shorter lead time (e.g. equation 1) the impact of the crash would be included in the fore-

[1] See Basi, Carey and Twark (1976: 247) for a comment on price based deflators in accuracy studies. Capstaff, Paudayl and Rees (1995: 72) also choose to use earnings as a deflator.

[2] Mean errors for each model in Chant (1980: Table 1) are: M1 = 0.3018, S&P425 = 0.3102, Bank loans = 0.3279, Random walk = 0.3097.

casting model. Since output and corporate profits generally increased during the period 1988–89, low or negative growth adjustments to random walk forecasts are likely to lead to inferior forecasts. For the three money supply measures, Equation 1 is the most accurate, indicating a one-year lead over corporate earnings.

To test the significance of error differentials, both the 'paired' or 'matched samples' t-test (parametric) and the Wilcoxon Signed Ranks test (non-parametric) for related samples, are utilised. These tests compare forecasts from two models in a pair-wise manner, relating to each of the 565 firm-year observations to identify significant differences. These related-sample tests benefit from the fact that for each particular firm-year observation, the only source of variation in accuracy is the difference in the two models being compared. These statistics are used to compare errors for each lead indicator model, with the errors for a random walk model. For the paired t-test, the null and alternative hypotheses are stated below:

H_0: *Mean error (lead indicator)—Mean error (random walk) = 0*

H_1: *Mean error (lead indicator)—Mean error (random walk) $\neq$ 0*

The test is conducted as a two-tail test, since the lead indicator models could outperform or under-perform the random walk model. The Wilcoxon Signed Ranks test investigates a similar hypothesis, but since this non-parametric test is based on error rankings instead of means, the hypotheses are stated more generally as:

H_{0-}: *Error distributions for lead indicator model and random walk model are identical.*

H_1: *Error distributions for lead indicator model and random walk model are not identical.*

In Table 1, mean and median error values are presented for the unadjusted random walk, and the five lead indicator models. Both Wilcoxon Signed Ranks and paired t-test statistics are also presented, which provide a test of each model against the unadjusted random walk. Table 1 shows that the M4 money supply model generates the lowest values for both the mean and median errors, with the bank loans model proving the least accurate—reinforcing some of the findings of Chant's US study (see footnote 2).

Having identified the most appropriate form of model for each lead indicator, Wilcoxon Signed Ranks and paired t-tests are conducted to allow pair-wise comparisons between all the lead indicator models. This should allow identification of the lead indicator model with the most consistent performance. These test statistics are presented in Table 2.

The results in Table 2 provide further evidence of the M4 money supply model's superiority over the other lead indicators. The potential lead indicator properties of M4 are discussed later. The 'next best' model is the FTSE-100 index model. There are several reasons why the M4 money supply model may be superior: first, the lead indicator properties for stock indices have been subjected to some criticism, especially since the 1987 crash. Zarnowitz (1992: 354–355) describes how US studies from the early 1980s were generally supportive of the stock market's lead indicator properties for economic activity, but that studies from the late 1980s and early 1990s give mixed or negative results. Second, it may be that the money supply is more sensitive in reflecting very short term economic fluctuations that may have minimal impact on the value of the stock market, but which may influence the earnings for a single year. Thus, the money supply may signal short–term, temporary (i.e. transient) impacts on earnings numbers. Transitory components of earnings may have a noticeable impact on a single year's earnings, but (by their transient nature) are likely to have no significant impact on corporate valuation.

3.2. Lead indicator (money supply) model vs. financial analysts

In practice, professional investors obtain their forecasts from financial analysts. Analysts' forecasts offer a more demanding yardstick against which to test the performance of the money supply model. The model is tested against the most recently created analysts' forecasts available at short term horizons (8, 9, 10 and 11 months) and long term horizons (12, 15, 18 and 23 months) prior to the announcement of earnings for the fiscal year being forecasted. Generally, the 12-month horizon coincides with the announcement of the previous years' earnings[3]. Evidence from the US (Brown and Rozeff, 1978) and the UK (Patz, 1989) suggest that at horizons greater than 12 months, analysts' forecasts are not superior to random walk forecasts.

At horizons greater than 12 months, the data used in the random walk model (current year's earnings, A_t) have usually not yet been released, so such tests are biased against analysts to some extent. For horizons of less than 12 months, it would be expected that analysts should outperform a simple model, since the analyst has access to all the information contained in the model, including the relevant money supply data. UK studies by Bhaskar and Morris (1984) and Patz (1989) indicate significant analyst superiority over random walk forecasts, at horizons less than 12 months. Using the same statistics employed in the previous analysis—mean and median error, and Wilcoxon and paired t-tests statistics—the money

[3] Inspection of the year-ends and announcement dates suggests little change in these dates for fiscal years t and t+1 for this data set.

Table 1
Lead indicator models vs. random walk model

Sample: 565 firm-year forecasts

Variables and models:

Error metric:	$\lvert\hat{A}_{t+1} - A_{t+1}\rvert / A_{t+1}$
Random walk:	$\hat{A}_{t+1} = A_t$
Bank loans:	$\hat{A}_{t+1} = A_t(1+\Delta BL_{GM})$
FTSE-100:	$\hat{A}_{t+1} = A_t(1+\Delta FTSE_{t-2})$
Money (MO):	$\hat{A}_{t+1} A_t(1+\Delta MO_t)$
Money (M2):	$\hat{A}_{t+1} = A_t(1+\Delta M2_t)$
Money (M4):	$\hat{A}_{t+1} = A_t(1+\Delta M4_t)$

Where		
	$A_t =$	actual earnings for fiscal year t
	$\hat{A}_{t+1} =$	forecast of earnings for fiscal year t+1
	$\Delta BL_{GM} =$	geometric mean change in bank loans, for fiscal years t-2, t-1 and t
	$\Delta FTSE_{t-2} =$	change in FTSE-100 index during fiscal year t-2
	$\Delta M0_t =$	change in M0 money supply during fiscal year t
	$\Delta M2_t =$	change in M2 money supply during fiscal year t
	$\Delta M4_t =$	change in M4 money supply during fiscal year t

Model	Mean Error	Median Error	Model vs. Random walk: *Wilcoxon Signed Rank Statistic*	Model vs. Random walk *Paired t-test Statistic*
Random Walk	0.2628	0.2003	—	—
Bank Loans	0.2590	0.1506	−3.51**	−0.41
FTSE-100	0.2208	0.1101	−7.73**	−6.65**
Money Supply M0	0.2412	0.1616	−10.39**	−9.73**
Money Supply M2	0.2196	0.1196	−8.84**	−9.27**
Money Supply M4	0.2164	0.1071	−8.20**	−8.36**

Positive Wilcoxon Signed Ranks statistics and paired t-test statistics indicate superiority of a random walk model, compared to the model listed down the left side.
Negative values indicate superiority of the model listed down the left side.
All statistical tests utilise a two-tail test:
**indicates rejection of *null* (no difference) hypothesis at the 0.05 level.

supply model is tested here against analysts' forecasts.

If there is an analyst-model differential, there are reasons to expect it to be related to firm size (i.e. market value). There is much evidence that the collection and dissemination of information by market professionals is a positive function of firm size. Evidence from both share price returns and analysts' forecasts indicates that earnings announcements are relatively less timely information sources for large firms. Atiase (1985) and Bamber (1986) investigate variation in returns and trading volume respectively, around earnings announcements. The impact of an announcement on these variables is significantly greater for small firms than for large firms. A study of abnormal returns profiles by Freeman (1987) finds that for large firms, share prices begin to incorporate information about forthcoming earnings announcements at much greater horizons than for small firms. Further evidence of this firm size effect is presented by Bhushan (1989a), who finds that the marginal information content of earnings announcements is a negative function of a firm's market value. Attempts to predict future earnings numbers using price data also reveal greater information content in the prices of large firms (see Collins et al., 1987).

Evidence of a size effect can also be found from the direct examination of earnings forecasts generated by financial analysts. Brown et al., (1987) compare analysts' earnings forecasts with forecasts generated by time series models. Analyst superiority is found to be a positive function of firm size. Stickel (1989) investigates analysts' revision activity around the time of interim earnings an-

Table 2
The relative performance of lead indicator models in pair-wise tests

Sample: 565 firm-year forecasts

Variables and models: See Table 1.

Model	FTSE-100	Money Supply M0	Money Supply M2	Money Supply M4
Bank Loans	+6.19**	+0.60	+4.99**	+6.32**
	+7.50**	+2.29**	+6.63**	+8.21**
FTSE-100		−6.23**	−1.45	+0.90
		−4.39**	+0.46	+2.25**
Money Supply M0			+6.59**	+6.01**
			+8.00**	+6.73**
Money Supply M2				+3.23**
				+2.25**

First statistic in matrix: Wilcoxon Signed Ranks test
Second statistic in matrix: Paired t-test

Positive Wilcoxon Signed Ranks statistics and Paired t-test statistics indicate superiority of the model along the top of the matrix, compared to the model listed down the left side. Negative values indicate superiority of the model listed down the left side.
All statistical tests utilise a two-tail test:
**indicates rejection of *null* (no difference) hypothesis at the 0.05 level.

nouncements; revision activity is negatively related to firm size, indicating that interim announcements for large firms are relatively less timely information sources. A number of UK studies, such as Patz (1989) and Capstaff et al. (1995), indicate that at a given horizon analysts' forecasts for large firms are superior to those for small firms. All these studies provide evidence of a size effect in operation with regard to information collection and dissemination. There are various factors that may explain this phenomenon:

(a) There are potentially greater financial gains for market professionals, in the identification of mispriced securities for firms with large market values:

> '[K]nowledge that a large firm's common stock is mispriced by one per cent could be used to earn greater profits than information that would generate a one per cent adjustment in the market value of a small firm's common equity.' (*Freeman, 1987: 196*)

In addition, once an investor has identified a mispriced security, any trading activity is likely to be more noticeable (thereby revealing the informed investor's information to other market participants) for small or thinly-traded firms. Thus, the opportunities for profitable trading are likely to be more limited for small firms (see Freeman, 1987: 197–99; Bhushan, 1989b: 261).

(b) The greater economic incentives for large firms leads to analyst-following being a positive function of firm size. Analyst-following is modelled and empirically investigated by Bhushan (1989b). The increased analyst-following for large firms leads to increased competition among analysts. Trueman (1990) suggests that analysts may have incentives not to include all the private information they currently possess in their forecasts, resulting in bias and reduced accuracy. However, Cheung (1990) argues that this problem is unlikely to occur where there are large numbers of competing analysts, i.e. less likely to occur for large firms.

(c) The amount of information disseminated to investors through publications like the *Wall Street Journal* (which are more timely information sources than earnings announcements) is a positive function of firm size (Thompson, Olsen and Dietrich 1987).

The results of this study support the hypothesis that firm size is an important factor determining analyst superiority over simple models. Table 3 presents the mean and median errors for analysts, at the eight forecast horizons, and also presents Wilcoxon Signed Ranks and paired t-test statistics indicating how analysts compare with the M4 money supply model.

Table 3 shows that for the total sample of firms, the mean and median error values, and the test statistics, favour the money supply model where analysts are forecasting 15 months ahead or more. Only at the 12 month horizon is analyst superiority evidenced. Nevertheless the comparison of

Table 3
Forecast errors: financial analysts' vs. money supply (M4) model

All firms sample: 565 firm-year forecasts.
- Small firms = lower quartile of firm-years by market value (<£131m).
- Large firms = upper quartile of firm-years by market value (>£1519.37m).

Analysts' forecasts are examined at eight different horizons, relative to the announcement data which is available at around the 12-month horizon.

First statistic in matrix:	Mean error
Second statistic in matrix:	Median error
Third statistic in matrix:	Wilcoxon Signed Ranks test statistic (analysts vs. money supply model)
Fourth statistic in matrix:	Paired t-test statistic (analysts vs. money supply model)

	Analysts 23 months	*Analysts 18 months*	*Analysts 15 months*	*Analysts 12 months*	*Analysts 11 months*	*Analysts 10 months*	*Analysts 9 months*	*Analysts 8 months*	*Money supply model*
All firms									
Mean:	0.2713	0.2561	0.2350	0.1993	0.1893	0.1841	0.1706	0.1597	0.2146
Median:	0.1463	0.1186	0.1088	0.0850	0.0788	0.0725	0.0683	0.0625	0.1071
Wilcoxon:	−7.72**	−3.87**	−1.23	+5.29**	+7.18**	+8.16**	+9.35**	+9.86**	—
Paired t:	−6.44**	−4.59**	−2.35**	+2.33**	+3.84**	+4.48**	+5.88	+7.07**	—
Small firms									
Mean:	0.4149	0.4136	0.3963	0.3329	0.3169	0.3151	0.2876	0.2661	0.3293
Median:	0.2169	0.1755	0.1619	0.1089	0.1089	0.1057	0.0991	0.0991	0.1549
Wilcoxon:	−3.65**	−3.26**	−2.08**	+2.17**	+2.77**	+3.04**	+3.85**	+4.12**	—
Paired t:	−3.85**	−3.71**	−2.97**	−0.18	+0.67	+0.74	+1.965*	+2.89**	—
Large firms									
Mean:	0.1705	0.1595	0.1315	0.1248	0.1211	0.1144	0.1097	0.1047	0.1548
Mean:	0.1066	0.0816	0.0765	0.0643	0.0642	0.0568	0.0525	0.0517	0.0874
Wilcoxon:	−2.10**	+0.55	+1.949*	+3.26**	+3.84**	+4.16**	+4.57**	+4.86**	—
Paired t:	−1.09	−0.30	+1.961*	+2.71**	+3.03**	+3.78**	+4.25**	+4.59**	—

Variables and models: see Table 1.

Positive Wilcoxon Signed Ranks statistics and Paired t-test statistics indicate superiority of analysts' forecasts; negative values indicate superiority of the money supply model.
All statistical tests utilise a two-tail test:
**indicates rejection of *null* (no difference) hypothesis at the 0.05 level.
*indicates rejection of *null* (no difference) hypothesis at the 0.052 level,

large and small firm sub-samples illustrates an apparent firm size effect, similar to that documented in studies like Brown, Richardson and Schwager (1987); the superiority of analysts is an increasing function of firm size. For small firms, the first evidence of analyst superiority is detected at the 12-month horizon, where comparison of median errors and a significant Wilcoxon Signed Ranks statistics indicate analyst superiority. However, the paired t-test statistic and comparison of mean errors indicates little difference (indeed, a small superiority for the money supply model). In fact, for small firms, the paired t-test statistic only indicates 'borderline-significant' analyst superiority at the nine month horizon.

The results for large firms display a very different time-profile for accuracy. For large firms, the only evidence of model superiority is when comparison is made with the longest term analysts' forecasts, made 23 months prior to an announcement. Analyst superiority emerges as 'borderline-significant' at the 15-month horizon, for both the Wilcoxon and paired t-tests.

4. Discussion and additional issues

This section expands on a number of issues which flow from the main analyses of this study.

4.1. Do changes in M4 contain information beyond that contained in firm-specific changes?

In order to examine this question, a random-walk-with-drift (RWD) model is employed as an additional source of forecasts. The drift term in equation 6 is simply the previous year's growth rate for annual earnings. This model form has been utilised in a number of studies (e.g. Patz, 1989):

$$\hat{A}_{t+1} = A_t\,(1 + \Delta A_t) = A_t\left(\frac{A_t}{A_{t-1}}\right) \qquad (6)$$

where the variables are as defined previously.

The form of the RWD model in equation 6 mirrors that of the money supply model, except that the adjustment factor uses firm-specific data (i.e. earnings numbers A_t and A_{t-1}) rather than macroeconomic data. The RWD model can be compared with the money supply (M4) model, and with the simple random walk model, on the basis of mean and median errors, and Wilcoxon and paired t-test statistics; these results are presented in Table 4.

The results shown in Table 4 are mixed. The mean error and paired t-test favour the random walk over the RWD, while the median error and Wilcoxon Signed Ranks tests favour the RWD. However, when comparing the RWD and the money supply model, all statistics indicate the significant superiority of the money supply model. This superiority over the RWD indicates that changes in broad money contain incremental predictive information, relative to similar changes in an individual firm's earnings over the same time period. This result is consistent with Chant, who finds that the money supply model outperforms models which utilise past earnings data (average-growth and exponential-smoothing models).

4.2. Money as a lead indicator for UK corporate earnings

An important point to note is that lead indicator variables need not cause (or be strongly structurally linked with) the target variable under study; all that is required is that they provide accurate signals regarding changes in the target variable.

> '[A]n indicator need not necessarily have any well-defined *steady-state* structural relation with the final target; it need only possess *short-run* information, which complements or extends the existing forecast information set'. (Astley and Haldane, 1995: 8).

Thus, the use of a lead indicator is acceptable for forecasting purposes even without a strong theoretical framework to link the lead and target variables.

Table 4
Random-walk-with-drift vs. random-walk and money supply (M4) models.

Sample: 565 firm-year forecasts

First statistic in matrix:	Mean error
Second statistic in matrix:	Median error
Third statistic in matrix:	Wilcoxon Signed Ranks test statistic
Fourth statistic in matrix:	Paired t-test statistic

Model:
Random walk with drift: $\hat{A}_{t+1} = A_t(A_t/A_{t-1})$
where variables and other models are as defined in Table 1.

	Random walk with drift	*Random walk*	*Money supply M4*
n = 565			
Mean:	0.3008	0.2628	0.2164
Median:	0.1207	0.2003	0.1071
Wilcoxon:	—	−2.68**	+5.22**
paired t:	—	+2.54**	+6.26**

Positive Wilcoxon Signed Ranks statistics and Paired t-test statistics indicate superiority of random walk or money supply model; negative values indicate superiority of the random-walk-with-drift.
All statistical tests utilise a two-tail test:
**indicates rejection of *null* (no difference) hypothesis at the 0.05 level.

There is much evidence that money aggregates act as lead indicators for national income measures and prices in the UK (e.g. Crockett, 1970; Breedon and Fisher, 1993; Henry and Pesaran, 1993; Astley and Haldane, 1995). However, providing a structural explanation for the lead indicator properties of money is difficult (Breedon and Fisher 1993: 31). Astley and Haldane examine the lead indicator properties of both M0 and M4 for a range of economic variables with a 12-month lag, using Granger-causality tests.

Their main results (Astley and Haldane: 49–50) indicate that M0 is a superior lead indicator for GNP, but a disaggregated analysis indicates that M4 proves an effective indicator for certain sectoral variables, including production industries output. A study by Dale and Haldane (1995: 1621), who analyse monthly UK data for 1974–92, concludes that in the short run, money sends timely signals regarding corporate output movements. This work will undoubtedly be extended in the future and may provide more detailed insights into the potential links between monetary aggregates and corporate sector activity/income.

4.3. Future research

The models employed here imply a simple one-for-one mapping of money supply changes onto earnings numbers which is almost certainly a simplification of reality. Indeed, lead indicators are usually chosen for their ability to predict the *direction* of trends and the *timing* of turning points for a target variable, rather than to predict the *magnitude* of changes. The fact remains that both this UK study, and the US study by Chant, indicate that these simple models can outperform the venerable random walk model (and average growth models), both in terms of overall mean errors and in pair-wise statistical tests.

The study of lead indicators through the predictive gains to augmented random walk models is a relatively simple method of analysis; it may be that alternative analytical methods may shed additional light on the relationship between lead indicators and corporate activity/income, although the lack of available data may pose a problem. For example, the use of the Granger-causality tests used in macroeconomic studies, or the incorporation of lead indicators into sophisticated time series models, may prove difficult when studying annual earnings numbers because of the low number of observations that can be collected for most UK firms.

Another aspect that may be considered is the impact of firm characteristics on the accuracy of lead indicator models. The results in Table 3 here show that the money supply model generates more accurate forecasts for large firms than for small firms (although analyst superiority is greater for larger firms). On the assumption that smaller firms are generally more risky, in terms of earnings variation and covariation with the market, it may be that this result illustrates the impact of risk on the effectiveness of the money supply model.

Because the money supply model used here is relatively easy for researchers to construct, and does not require information which may be unavailable in the UK (e.g. quarterly earnings numbers) or variable in quality (e.g. reported segment data), it offers an alternative yardstick to the much used random walk and average growth models for researchers investigating the relative accuracy of managers' or analysts' forecasts.

6. Conclusion

The results of this study suggest that a number of economic variables—particularly the broad monetary aggregate M4—act as lead indicators for UK corporate earnings numbers, across the period 1986–89. The results here show that a simple adjustment to a random walk forecast generates a significant improvement in accuracy. In addition, leading changes in broad money appear to contain greater predictive ability than equivalent changes in a firm's annual earnings. These results appear to confirm the results obtained by Chant (1980) for US companies across 1968–77, which suggest predictive gains to money supply data[4].

The performance of the money supply model, relative to financial analysts, is size dependent. For large firms, analyst superiority emerges at around 15 months prior to an announcement. For small firms, evidence of significant analyst superiority only exists at shorter horizons (indeed, only at the nine-month horizon when using parametric tests). This provides further evidence of a size-differential regarding information collection and dissemination by market participants. Overall, the results here suggest that the omission of economic data from the univariate time-series earnings models, frequently used in accounting research, may be a severe limitation to the predictive power of such models. For those concerned with the forecasting of corporate earnings, there may be greater gains from the further development of (relatively simple) models which use data additional to the earnings series, rather than the developing of ever-more exotic univariate models (e.g. non-linear models) of the earnings process.

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[4] Of course, Chant only considers the relatively narrow US monetary aggregate M1.

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