# DETERMINANTS OF THE BIAS AND INACCURACY OF MANAGEMENT EARNINGS FORECASTS

Andrew A. Anabila, University of Texas – Pan American
EunYoung Whang, University of Texas – Pan American

**ABSTRACT**

*The safe harbor provisions have increased over the years, following the Private Securities Litigation Reform Act (PSLRA) of 1996 and the Securities Litigation Uniform Standards Act (SLUSA) of 1998. The objective is to encourage more earnings guidance by managers. However, a number of firms like Coca Cola and Gillette moved to abandon quantitative earnings forecasts, due to concerns over the markets' response when they miss their forecasts. This study examines the determinants of management earnings forecasts bias and inaccuracy. The evidence suggests that forecast bias and inaccuracy are not systematically associated with diversification however, are associated with the fraction of nonoperating assets. Also, capital structure, audit quality and institutional holdings are systematic determinants of forecast bias and inaccuracy. Finally, industry attributes of munificence, dynamism and concentration are indicators of inherent imperfections of management forecasts, but are exogenous to management's control. The reasons for, and implications of these findings are discussed.*

**JEL:** M41, M48

**KEYWORDS:** Management Forecasts, Bias, Inaccuracy, Determinants, Litigation Costs, Safe Harbor, Munificence, Dynamism, Concentration. All Data Are Available from the Public Sources Mentioned

## INTRODUCTION

Management earnings forecasts are very important for many reasons. They help to guide the public and analysts to predict firms' earnings (Baginski and Hassell, 1990, Baginski, Conrad and Hassell, 1993, Pownall, Wasley and Waymire, 1993). They are used by managers to reduce information asymmetry prior to issuing securities (Frankel et al., 1995). They influence market expectations about firm value (Patell, 1976, Penman, 1980), and about industry earnings (Bosall IV et. al., 2013). However, users who feel hurt, say by the bias and inaccuracy of the forecasts, often sue the managers for deceit. In fact two securities litigation reform laws on safe harbor have been enacted (in 1996 and 1998) to help protect managers from any wrongful legal action by users. Also, the Regulation Fair Disclosure forbids managers from providing selective guidance to analysts. However, these regulations seem inadequate for encouraging managers to issue earnings forecasts since the majority of firms do not issue forecasts and some of those that used to issue are discontinuing such activity (Byrnes, 2003, Deloitte, 2009). Proper policy that will ensure an enabling environment for the free flow of information like earnings guidance requires a systematic examination of forecast errors for their determinants. This study examines the association between firms' earnings-relevant economic factors and management earnings forecast bias and inaccuracy. The economic factors include the nature of business activities, the structure of the industry, and the measurement and disclosure controls that impact on the firm's information environment. This study is further motivated by the fact that prior research seems to assume that management forecast attributes are driven largely by managerial incentives. However, managers are not only financial information suppliers but also corporate decision makers, whose information processing capabilities influence all dimensions of corporate endeavors (Gong et al., 2011).

Specifically, both internal and external factors impact on all dimensions of managerial decisions, and through that, the earnings amount and expectations thereof. The factors include the firm's industry structure and its economic activities that give rise to the earnings. They also include factors that impact on the measurement and disclosure of the earnings, such as the extent of managerial disclosure discretion, apart from managerial incentives to issue misleading actual and forecast earnings. Consider for example an argument that managers manage earnings to beat forecasts. Though this sounds possible, high audit quality and pressures from institutional holders should render this less probable. A true assessment of the determinants of forecast attributes begins with an analysis of factors that determine the properties of the earnings and for that matter the earnings expectations.

Firms' actual and forecast earnings-relevant economic activities can be classified into operating, investing and financing. For these activities, we consider both geographic and line of business diversification (complexity of operations), non-operating assets relative to total assets (for investments), and capital structure using leverage (for financing), respectively. These are based on prior research (Thomas, 2002, Duru and Reeb, 2002, Anabila, 2012, Myers, 2001), on the implications of these factors for firms' earnings realizations and expectations. For firms' disclosure quality, we consider audit quality and pressure by institutional shareholders, because these constrain management reporting discretion (Behn et al., 2008, Piotroski and Roulstone, 2004). Also, industry concentration, munificence, and dynamism, which prior research has virtually ignored, are important external factors that provide a context for firms' earnings possibilities. We obtain annual management forecasts for 1995 through 2008 from *FIRSTCALL*, and financial and diversification data from *COMPUSTAT*. We consider only point management forecasts issued within the fiscal year for the fiscal year and we use the last of such forecasts. The foregoing criteria yield 3,894 firm-years (annual observations) for the analysis.

Our results are as follows. First, management forecasts exhibit a mean optimism bias (forecasts are greater than actuals). This has the potential to expose the firms to litigation. Second, the evidence shows that unlike analysts' earnings forecasts (Thomas, 2002, Duru and Reeb, 2002), management forecast bias and inaccuracy are not significantly associated with diversification. Thus, the implications of diversification for analysts' forecasts as per prior studies are likely due to subjective use of management forecasts. Analysts should decipher information from management forecasts objectively, rather than compromise quality to curry management's favor (Feng and McVay, 2010).

Third, forecast bias is positively (negatively) associated with investment in nonoperating assets (leverage, institutional holdings, audit quality, industry competition, dynamism and munificence). Forecast inaccuracy is negatively (positively) associated with investment in nonoperating assets and institutional holdings (leverage, audit quality, industry concentration, dynamism and munificence). These results suggest that nonoperating investments help management to beat their forecasts and reduce forecast absolute errors. This is because such assets are relatively liquid and can be readily mobilized and redeployed by management in pursuit of reporting objectives. Therefore, users should pay particular attention to firms' nonoperating activities that are of a continuing nature when forecasting earnings. Also, institutional holders seem to pressure management to be optimistic and to make less forecast errors. The results also suggest that leverage (due to the external monitoring that it engenders and the interest expense that it imposes), and audit quality, prevent management from managing earnings to beat expectations and to reduce forecast errors. The results relating to industry attributes draw attention to earnings relevant external factors outside the firm's control. Industries that are more concentrated (SHERF), feature fast growth (MUNIF), and are unstable or volatile (DYNAM) as defined by Boyd (1995), characterize more biased and erroneous forecasts. Users like analysts should research the earnings prospects of firms in such industries, rather than rely on management for earnings guidance.

We defer further discussion of the results, including those on the control variables of size, forecast horizon and forecast frequency, to the results section. This study further contributes to the literature as follows. First, prior research generally assumes that forecast attributes are driven largely by managerial incentives. But this study relates forecast attributes to the firm's earnings-relevant activities, measurement and disclosure quality, and industry attributes. It identifies factors such as industry attributes and institutional holdings that present inherent earnings uncertainty and pressure management to adopt a particular earnings outlook. The impact of these determinants explains in part why some firms do not issue earnings forecasts, suggesting that managers really need further protection in order to issue forecasts. Users should control for such factors to reduce their exposure to management forecast imperfections. The study proceeds as follows. The next section reviews the literature and states the hypothesis. The third section describes the methodology and data, and the fourth discusses the results. The fifth section summarizes and concludes.

## LITERATURE REVIEW AND STATEMENT OF HYPOTHESIS

### Prior Research

Various studies have examined management earnings forecast attributes from different perspectives and contexts. One such perspective borders on the frequency and availability of forecasts. Kile et al. (1998) shows that management earnings forecasts, especially non-quantitative ones, are frequently disclosed. Frankel et al. (1995) show that firms that access the capital markets disclose earnings forecasts more frequently to mitigate information asymmetry before the offering. Waymire (1985) shows that firms with less volatile earnings issue forecasts more frequently, and earlier in time than firms with more volatile earnings. This is because the high earnings volatility exposes the firm to litigation costs and loss of reputation, and the frequent disclosures are meant to revise the forecasts for new information to reduce such costs. Baginski et al. (2002) suggest that a greater frequency of management forecasts is associated with a less litigious environment (Canada) than a more litigious one (USA).

Another perspective of the literature shows that management forecasts are informative to analysts and investors about future earnings prospects and firm value (Patell, 1976, Penman, 1980, Jennings, 1987, Pownall et al., 1993, Baginski and Hassell, 1990). Frankel et al. (1995) document a strong interest on the part of management to disclose forecasts in order to reduce information asymmetry between managers and the public, prior to equity offerings. Others show that the information content increases with the accuracy of prior management earnings forecasts (Williams, 1996). More recently, Bosall IV et al. (2013), show that management forecasts contain macroeconomic information on the industry, beyond the firm-specific information. The usefulness of the forecasts however is limited by at least two different but linked themes. First is the limited availability of the forecasts. Second is the attributes, such as the inaccuracy and bias of the forecasts. Often, the market reacts negatively to the inaccuracy, and users who are hurt by the bias and inaccuracy of the forecasts resort to litigation against the management. However, the potential usefulness of the forecasts prompted the Private Securities Litigation Reform Act (PSLRA hereafter) of 1995, followed by the Securities Litigation Uniform Standards Act (SLUSA) of 1998.

These laws increased the safe harbor provisions to motivate managers to issue earnings forecasts. Despite the broader protection offered managers by the new legislature, a few firms disclose quantitative management earnings forecasts while some of the disclosing firms moved to stop disclosing such forecasts, citing the users' negative reaction to the forecast attributes (Deloitte, 2009, Byrne, 2003, Pownall et al., 1993). How can managers be effectively encouraged to provide earnings forecast guidance without fear of the users' reaction? For the most part, research studies on the properties of management forecasts have examined the managerial incentives and the credibility of the forecasts. For example, Irani (2003) shows that distressed firms' forecasts are optimistic. Rogers and Stocken (2005), show that the credibility of the forecasts decreases with management's likelihood of facing litigation, the ability to profit from insider trading, and the opportunity to shift risk for financially distressed firms. However, the public's ability to detect whether management forecasts are misleading limits management's ability to pursue those incentives through the forecasts. Feng and McVay (2010) document evidence showing that analysts' compromise their forecasts quality by overweighting management forecasts to curry favor from management for investment banking business. Some studies highlight circumstances under which management earnings forecasts may be more useful and credible. For example, Hirst et al. (2007) shows using experimental tests that disaggregated management forecasts (forecast of earnings coupled with components such as sales, cost of sales, selling and administrative expenses) are perceived to be more credible, clear and a mark of financial reporting quality, compared to aggregated forecasts.

Most of the foregoing research assumes rather interestingly that management has absolute control over the forecast attributes. However, Gong et al. (2011) find that management forecast errors (bias) persist over time, are unavoidable in a world of uncertainty yet have implications for the efficiency of managerial decision making. Understanding the forecast properties enables users to better utilize the forecasts, because managers are both corporate decision makers and financial information suppliers whose information processing capability impacts on all dimensions of corporate earnings-relevant decisions including operations, investments, and financing (Gong et al., 2011). Given the significance of management forecasts, identifying the determinants of the forecast errors could help analysts and the public to assess the reliability of the forecasts and the reasons for their properties. Knowledge of the determinants could also help guide the effort towards encouraging managers to issue earnings forecasts. This study seeks to contribute in this regard.

## Statement of Hypothesis

Prior studies by Thomas (2002) and Duru and Reeb (2002) suggest that the complexity of operating activities, namely, line of business and geographic diversification have implications for earnings expectations. Those studies focus on analysts' forecast attributes. Following those studies, we conjecture that management forecast bias and inaccuracy are each positively associated with diversification. Anabila (2012) also shows in the context of analysts' forecasts that nonoperating activities (investments) relative to operating activities has implications for earnings expectations. Investments are more liquid (compared say to machinery) and so management can readily move them to the most profitable area in pursuit of their earnings objective, including beating management forecasts. Arguably, such assets are less linked to managerial ability since they are not operated by management. Therefore, we conjecture that forecast bias and inaccuracy are positively associated with nonoperating assets relative to total assets.

Disclosure quality or information environments, all things being equal, are higher for firms that are subject to monitoring by lenders (Myers, 2001), have higher audit quality due to being audited by the BIG 4 (Behn et al., 2008), and have higher institutional holdings (Piotroski and Roulstone, 2004). Firms with higher values of these factors would be pressured to be optimistic but would have limited room to manipulate earnings towards a reporting objective. Therefore, we conjecture that bias and inaccuracy are each associated with leverage, audit quality, and institutional holdings.

Industry structure is generally external to the firm and the higher the uncertainty, the higher the forecast errors. Prior research has not generally related this to differences in management forecast properties. We conjecture that forecast bias and inaccuracy are associated with concentration (no competition), munificence (abundance of resources) and dynamism (instability in the industry) as defined by Boyd (1995). Based on all the foregoing, we hypothesize in null form that:

*H1. There is no relation between management forecast bias on one hand and diversification, investments, financial leverage, disclosure quality and industry concentration, munificence and dynamism, on the other.*

*H2. There is no relation between management forecast inaccuracy on one hand and diversification, investments, financial leverage, disclosure quality and industry concentration, munificence and dynamism, on the other.*

## METHODOLOGY AND DATA

Methodology

We examine first the respective correlations between the forecast attributes and the determinants. We then estimate a multiple regression that explains these forecast attributes using the determinants and controlling for prior determinants of the forecast attributes. The hypothesis purports to explain forecast attributes (bias and inaccuracy) using complexity of operations (diversification), nonoperating assets (investments), financing (leverage), audit quality (BIG 4 dummy), institutional holdings (institutional percent ownership), industry features (concentration, munificence and dynamism). We control for size, forecast horizon, and number of forecasts identified in prior research (e.g. Gong et al., 2011). We use the following models:

$$\begin{aligned} BIAS_{i,t} &= \alpha_0 + \alpha_1 * BUSSD_{i,t-1} + \alpha_2 * GEOSD_{i,t-1} + \alpha_3 * NONAS_{i,t-1} + \alpha_4 * LEV_{i,t-1} \\ &+ \alpha_5 * BIG4_{i,t-1} + \alpha_6 * INSTPCS_{i,t-1} + \alpha_7 * SIZA_{i,t-1} + \alpha_8 * HORIZON_{i,t} \\ &+ \alpha_9 * OBSCIG_{i,t} + \alpha_{10} * SHERF_{i,t-1} + \alpha_{11} * MUNIF_{i,t-1} + \alpha_{12} * DYNAM_{i,t-1} + \varepsilon_{i.t} \end{aligned} \quad (1)$$

and

$$\begin{aligned} FACC_{i,t} &= \alpha_0 + \alpha_1 * BUSSD_{i,t-1} + \alpha_2 * GEOSD_{i,t-1} + \alpha_3 * NONAS_{i,t-1} + \alpha_4 * LEV_{i,t-1} \\ &+ \alpha_5 * BIG4_{i,t-1} + \alpha_6 * INSTPCS_{i,t-1} + \alpha_7 * SIZA_{i,t-1} + \alpha_8 * HORIZON_{i,t} \\ &+ \alpha_9 * OBSCIG_{i,t} + \alpha_{10} * SHERF_{i,t-1} + \alpha_{11} * MUNIF_{i,t-1} + \alpha_{12} * DYNAM_{i,t-1} + \varepsilon_{i.t} \end{aligned} \quad (2)$$

where:

BIAS=forecast bias, FACC=forecast inaccuracy (both for forecast attributes); BUSSD=business segment diversification index, GEOSD=geographic segment diversification index (both for complexity of operations); NONAS=proportion of nonoperating assets, LEV=financial leverage, BIG4=BIG4 auditor dummy, INSTPCS=institutional shareholding percentage, SIZA=size, HORIZON=forecast horizon, OBSCIG=number of forecasts issued during the fiscal year for the fiscal year, SHERF=Herfindhal index of industry sales concentration, MUNIF=industry munificence, DYNAM= industry dynamism. The variables SIZA, HORIZON and OBSCIG are the control variables based on prior research identified in the literature review section. The computations of BUSSD and GEOSD are as follows:

$BUSSD_{i,t} = 1 - \sum_{j=1}^{J}\left[Sales_{i,t,j} / \left(\sum_{j=1}^{J} Sales_{i,t,j}\right)\right]^2$, $GEOSD_{i,t,k} = 1 - \sum_{k=1}^{K}\left[Sales_{i,t,k} / \left(\sum_{k=1}^{K} Sales_{i,t,k}\right)\right]^2$, for all jϵJ number of business segments and kϵK number of geographic segments, for firm i in year t. Of the industry attributes, SHERF is the sales Herfindhal index of concentration in the industry, computed as

$SHERF_{i,D} = \sum_{i=1}^{D}\left[Sales_{i,t,} / \left(\sum_{i=1}^{D} Sales_{i,t}\right)\right]^2$ for all iϵD, that is firms ‘i’ in industry group D. Munificence

(MUNIF) is a standardized measure of industry sales growth computed following Boyd (1995; 306) as the slope coefficient, divided by mean value. The munificence slope coefficients are based on a regression of time against industry sales value, estimated for a given year using the five preceding years’ data, and the mean value is the mean over the munificence years of the annual industry sales. Dynamism (DYNAM) is a standardized measure of the volatility of industry sales growth rate over the munificence period, i.e. the standard error of regression slope coefficient divided by the mean of the industry sales over the munificence period. MUNIF, DYNAM, and SHERF are based on 3-digit SIC in this study. Size is proxies for exposure to political costs such as litigation. The frequency of forecasts captures the number of revisions of forecasts as new information becomes available.

Data

We obtain the management earnings forecasts and actual earnings from the *FIRSTCALL CIG and Actuals files*. We consider all point management forecasts issued within the fiscal year for that fiscal year. For example, if a firm has calendar fiscal year 2005, we consider forecasts dated within January 1st, 2005 through December 31st, 2005. We use only the last of such forecasts for the firm for that fiscal year. We do not consider forecasts dated after the fiscal year in order to avoid preannouncements. Following prior research, we scale the forecasts bias and inaccuracy by price as of the beginning of the year (Baginski et al., 1993, Pownall et al., 1993, Williams, 1996). Specifically, for each firm year, we compute forecast bias and inaccuracy respectively as: FBIAS= (actual EPS – last forecast EPS)/beginning price, and FACC=absolute value of (FBIAS). From the *FIRSTCALL CIG* database, we also obtain: HORIZON (forecast horizon) = log (end of fiscal year less date of the last forecast); and OBSCIG (forecast frequency) = number of the forecasts issued within and for the fiscal year.

We obtain fundamental financial and industry data from the *COMPUSTAT* fundamental annual file and other sources follows: Price per share (for scaling forecasts and actual EPS) at the end of the prior fiscal year. SIZA = log (total assets) from *COMPUSTAT*, INSTPCS = the shares outstanding (excluding those without voting rights) held by institutions as per *THOMPSON FINANCIAL INSTITUTIONAL HOLDINGS* database as of 2006 (2006 data are used for 2007 and 2008), as a percentage of shares outstanding in *COMPUSTAT* at the end of the year; both BUSSD=business segment diversification, and GEOSD=geographic segment diversification, are computed as defined under the methodology section using *COMPUSTAT SEGMENT* files data; BIG4= 1 if audited by BIG 4, zero otherwise. The industry structure variables of MUNIF, DYNAM and SHERF are computed following the description under the methodology section, based on 3-digit SIC Codes using *COMPUSTAT* data. We winsorize forecast errors and the other financial variables values below (above) the second ($99^{th}$) percentile to the second ($99^{th}$) percentiles respectively. Our sample covers 1995 through 2008 fiscal years. Table 1 describes the sample selection steps.

Table 1: Sample Selection

| **Panel A: Number of firm-year (annual) observations – 1995 through 2008** | |
|---|---|
| Number of numeric management forecasts issued within the fiscal year, for the fiscal year. | 40,268 |
| Retaining only point numerical forecasts, only first and last forecast for each firm-year | 11,349 |
| Final: Firms-years (annual observations) at the intersection of *FIRSTCALL* and *COMPUSTAT*. | 3,894 |

*Management forecasts and actual earnings are obtained from the FIRSTCALL database, for fiscal years. Forecasts for each firm year must have been issued within the beginning to the end of the fiscal year, and for that fiscal year. All other financial data are obtained from COMPUSTAT Annual (Industrial, Full Coverage and Research) and Segment files.*

From Table 1, the final sample comprises 3,894 firm-years (annual observations) at the intersection of all the databases. The sample drops by nearly two thirds to the final sample when we require a minimum of two point forecasts issued within the fiscal year for the fiscal year. This suggests that even when firms issue point forecasts, they do not do so frequently.

Table 2 shows that the forecasts tend to be optimistic. This is because for the forecast errors or bias (BIAS), the mean is -0.7839, the minimum is -11.9024, and the 1st quartile is -1.0035, which have higher absolute values than the maximum of 5.3812, and the 3rd quartile of 0.1372. The tabulated forecast errors are small because of the scaling by price. Also, within the fiscal year and for firms that issue at least 2 forecasts (OBSCIG), the firms issue a mean (median) of 4.1361 (4) annual forecasts for the fiscal year. The forecast horizon (HORIZON) has a mean of 4.1785 and a median of 4.2047, which are quite close.

Table2: Summary Distribution of Main Test Variables

| Variable | Mean | St. Dev | Minimum | 1st quartile | Median | 3rd quartile | Maximum |
|---|---|---|---|---|---|---|---|
| $BIAS_t$ | -0.7839 | 2.1883 | -11.9024 | -1.0035 | 0.0000 | 0.1372 | 5.3812 |
| $FACC_t$ | 1.3298 | 2.9643 | 0.0000 | 0.0698 | 0.2468 | 1.3617 | 11.9024 |
| $INSTPCS_{t-1}$ | 0.6939 | 0.2561 | 0.0000 | 0.5732 | 0.7502 | 0.8785 | 1.0000 |
| $BUSSD_{t-1}$ | 0.2356 | 0.2804 | 0.0000 | 0.0000 | 0.0000 | 0.4932 | 0.8025 |
| $GESOD_{t-1}$ | 0.2334 | 0.2631 | 0.0000 | 0.0000 | 0.0786 | 0.4969 | 0.7588 |
| $SIZM_{t-1}$ | 8.0019 | 1.5007 | 4.8865 | 6.9174 | 7.8314 | 9.0055 | 12.0673 |
| $SIZA_{t-1}$ | 7.9091 | 1.5223 | 4.9573 | 6.7534 | 7.7744 | 8.8996 | 11.9166 |
| $BIG4_{t-1}$ | 0.9647 | 0.1846 | 0.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| $BIG4_t$ | 0.9625 | 0.1900 | 0.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| $HORIZON_t$ | 4.1785 | 0.7385 | 1.6094 | 4.0431 | 4.2047 | 4.3567 | 5.6095 |
| $OBSCIG_t$ | 4.1361 | 1.7112 | 2.0000 | 3.0000 | 4.0000 | 5.0000 | 10.0000 |
| $MUNIF_{t-1}$ | 0.0872 | 0.0729 | -0.1901 | 0.0478 | 0.0886 | 0.1309 | 0.2811 |
| $DYNAM_{t-1}$ | 0.0224 | 0.0218 | 0.0034 | 0.0093 | 0.0146 | 0.0271 | 0.1162 |
| $SHERF_{t-1}$ | 0.0889 | 0.0871 | 0.0084 | 0.0409 | 0.0552 | 0.0978 | 0.4932 |
| $LEV_{t-1}$ | 0.2329 | 0.1706 | 0.0000 | 0.0970 | 0.2211 | 0.3394 | 0.7482 |
| $NONAS_{t-1}$ | 0.0642 | 0.1119 | 0.0000 | 0.0000 | 0.0140 | 0.0700 | 0.5608 |

*N=3,894. Following is a description of how the variables are computed for each period t (t-1 implies the prior year). BIAS: actual EPS less last annual forecast issued by management (FIRSTCALL CIG_Est) before the end of the fiscal year, divided by price (COMPUSTAT annual data199) at the beginning of the year. FACC: absolute value of BIAS. INSTPCS: institutional shareholdings at the end of the year (excluding those without voting rights), as a percent of shares outstanding. HORIZON: log of number of days to the end of the fiscal year since the last annual forecast was made, BUSSD: 1 minus the sum of the squares of the sales of all the business segments divided by the square of the total sales, for the fiscal fiscal year. GEOSD: 1 minus the sum of the squares of the sales of the geographic segments divided by the square of the total sales, for the fiscal year, SIZA: log of total assets (in millions of dollars) as of the end of the period, BIG4 (not tabulated): dummy equal 1 if auditor of the corporation is a BIG4 audit firm, zero otherwise. OBSCIG: number of annual earnings forecasts issued within the year for the year. MUNIF: munificence or abundance of resources in the industry, operationalized as a standardized measure of industry sales growth computed as (See Boyd, 1995; 306) the regression slope coefficient, divided by mean value. Coefficients are based on regression of time against value of sales, estimated for a given year based on the five preceding years. DYNAM (Dynamism): the volatility within the industry, operationalized using a standardized measure of the volatility of industry sales growth rate over the munificence period, i.e. the standard error of regression slope coefficient divided by the mean sales. SHERF: extent of monopoly, or lack of industry competition (squares of sales of firms in the 3-digit SIC, divided by square of the sum of the sales in the SIC). Sales Hirschman-Herfindahl industry concentration index, computed as the sum of the squares of market shares (based on sales) of firms within a given industry. LEV: leverage, i.e. fraction of assets financed by debt (total debt/total assets). NONAS: nonoperating assets as a fraction of total assets.*

Since these represent about 65 and 67 days respectively, they suggest that on average, the last forecasts for the year are issued a little over two months to the year end, well within the fourth quarter of the year, but well before the year end. Therefore, they are not preannouncements. Most of the firms in the sample have BIG 4 auditors (BIG4 mean is 0.9625, median is 1), high institutional holdings (mean INSTPCS is 0.6939, median is 0.7502), significant leverage (mean LEV of 0.2329, some as high as 0.7482), and diverse proportions of nonoperating assets (mean NONAS of 0.0642, maximum of 0.5608).

## RESULTS

For a perspective of the univariate relations, we estimate and report correlation coefficients in Table 3. They are all Pearson coefficients. The observations are pooled (not sorted, say by year).

Since the results in this table are based only on pairwise correlation, they are meant to provide a basis for what to expect in the multivariate tests. For example, correlations amongst the independent variables would prompt tests for multicollinearity. From the table, BIAS is negatively associated with INSTPCS (-0.039), BIG4 (-0.054), LEV (-0.061), MUNIF (-0.065), DYNAM (-0.059) and SHERF (-0.034), but positively associated with BUSSD (0.040), GEOSD (0.052), and non-operating investment (0.066). Also, FACC is negatively associated with BIAS, INSTPCS, GEOSD, and NONAS but positively associated with BUSSD, BIG4, MUNIF, DYNAM, SHERF, and LEV. These stated extracts from the table focus on pairings of the dependent with the independent variables and generally support our conjectures under the prior research section. However, they need to be subjected to scrutiny in a multiple regression setting. Therefore, we skip further discussion of the implications, preferring instead to look at the implications of the relations amongst the independent variables. The table shows that some of the independent variables are significantly correlated. The following pairs are examples: BUSSD and INSTPCS, BIG4 and BUSSD, BIG4 and GEOSD, and LEV and INSTPCS. These necessitate tests for multicollinearity in the multiple regression setting where we assess the incremental association between the forecast attributes and the independent variables. The results of such tests are reported in Table 4 below.

Table 3: Correlation Coefficients for Main Test Variables

| **Panel A: Correlation between forecast bias and independent variables** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Variable | $BIAS_t$ | $INSTPCS_{t-1}$ | $BUSSD_{t-1}$ | $GEOSD_{t-1}$ | $BIG4_{t-1}$ | $MUNIF_{t-1}$ | $DYNAM_{t-1}$ | $SHERF_{t-1}$ | $LEV_{t-1}$ |
| $FACC_t$ | -0.580*** | | | | | | | | |
| $INSTPCS_{t-1}$ | -0.039** | | | | | | | | |
| $BUSSD_{t-1}$ | 0.040** | -0.037** | | | | | | | |
| $GEOSD_{t-1}$ | 0.052*** | 0.017 | 0.425*** | | | | | | |
| $BIG4_{t-1}$ | -0.054*** | 0.060*** | 0.083*** | 0.055*** | | | | | |
| $MUNIF_{t-1}$ | -0.065** | 0.059*** | -0.045*** | -0.025 | -0.013 | | | | |
| $DYNAM_{t-1}$ | -0.059*** | -0.084*** | -0.042*** | -0.224*** | 0.002 | -0.206*** | | | |
| $SHERF_{t-1}$ | -0.034** | -0.005 | -0.045*** | -0.194*** | -0.149*** | 0.118*** | 0.280*** | | |
| $LEV_{t-1}$ | -0.061*** | -0.046*** | -0.009 | -0.157*** | 0.078*** | -0.035** | 0.115*** | -0.051*** | |
| $NONAS_{t-1}$ | 0.066*** | -0.011 | -0.006 | 0.034** | 0.029* | 0.021 | -0.018 | -0.109*** | -0.148*** |
| ***Panel B: Correlation between forecast inaccuracy and independent variables*** | | | | | | | | | |
| Variable | $FACC_t$ | $INSTPCS_{t-1}$ | $BUSSD_{t-1}$ | $GEOSD_{t-1}$ | $BIG4_{t-1}$ | $MUNIF_{t-1}$ | $DYNAM_{t-1}$ | $SHERF_{t-1}$ | $LEV_{t-1}$ |
| $INSTPCS_{t-1}$ | -0.173*** | | | | | | | | |
| $BUSSD_{t-1}$ | 0.011** | -0.037** | | | | | | | |
| $GEOSD_{t-1}$ | -0.022 | 0.017 | 0.425*** | | | | | | |
| $BIG4_{t-1}$ | 0.095** | 0.060*** | 0.083*** | 0.055*** | | | | | |
| $MUNIF_{t-1}$ | 0.089** | 0.059*** | -0.045*** | -0.025 | -0.013 | | | | |
| $DYNAM_{t-1}$ | 0.078*** | -0.084*** | -0.042*** | -0.224*** | 0.002 | -0.206*** | | | |
| $SHERF_{t-1}$ | 0.058*** | -0.005 | -0.045*** | -0.194*** | -0.149*** | 0.118*** | 0.280*** | | |
| $LEV_{t-1}$ | 0.062*** | -0.046*** | -0.009 | -0.157*** | 0.078*** | -0.035** | 0.115*** | -0.051*** | |
| $NONAS_{t-1}$ | -0.060*** | -0.011 | -0.006 | 0.034** | 0.029* | 0.021 | -0.018 | -0.109*** | -0.148*** |

*This table reports Pearson correlation coefficients for the main test variables that are examined. The variables are defined in Table 2. Significance at 1% or better, 5% or better and 10% or better are denoted by ***, **, and * respectively.*

In Table 4, based on models 1 and 2 from the methodology section, we estimate separate regressions with forecast attributes (bias and inaccuracy respectively) on earnings relevant factors (operations, investments, and financing), disclosure quality and industry structure. In Panel A, we consider all the independent variables directly. In Panel B, we control for industry using dummies for which we do not report the test statistics, as is customary with most prior research. As suggested by the results discussed under Table 3 above, we estimate "Variance Inflation Factors" (VIF) in each model to infer the incidence of collinearity. Since the VIFs are all less than 2, the results are not afflicted by collinearity.

From the table, BUSSD and GEOSD are both insignificant in both Panels A and B. This suggests that for the sample, complexity of operating activities is not a determinant of management forecasts bias and inaccuracy. Since Thomas (2002) and in particular Duru and Reeb (2002) suggest that these firm attributes are associated with poor attributes of analysts' forecasts, then the differences in these results suggest that diversified firms characterize more information asymmetry between managers and the analysts. The table shows that NONAS (the proportion of investments) is positively associated with bias (1.1913 and 0.5960 in Panels A and B) but negatively associated with forecast inaccuracy (-1.3920 and -0.9400 in Panels A and B). This suggests that the relative liquidity of these assets compared to operating assets such as equipment and land, allows management to deploy them with more flexibility to source profits and meet or beat their own forecasts, and to reduce forecast errors. Similar to the results on diversification, this finding contrasts with prior research relating analysts' forecasts to investments

(Anabila, 2012). Financing structure (LEV) is negatively associated with bias (-0.7849 and -0.8198 in Panels A and B) but positively associated with forecast inaccuracy (1.1916 and 1.3563 in Panels A and B). This suggests that debt financing, likely due to the potential volatility introduced by the interest charge, reduces the predictability of earnings even by management. Further, the scrutiny of lenders makes it difficult for managers to manage earnings towards their reporting objective, which is to beat the forecasts. For disclosure quality, INSTPCS is negatively associated with forecast bias (-0.3483 and -0.2063 in Panels A and B) and negatively associated with inaccuracy (-2.1129 and -2.3319 in Panels A and B). These suggest that institutional holdings constitute a source of pressure on management to be optimistic but the managers are less capable of managing their earnings. Audit quality (BIG4) is negatively associated with bias (-0.1219 and -0.1459 in Panels A and B) but positively associated with inaccuracy (0.5079 and 0.4993). These suggest that clients of BIG 4 auditors are optimistic, but are also tend to be inaccurate in their predictions likely at least in part because their auditors limit their ability to manage their earnings to meet or beat their forecasts.

Table 4: Regression of Forecast Bias and Accuracy on Determinants

| | **Model 1** | | **Model 2** | |
|---|---|---|---|---|
| **Variable** | **Slope** | **VIF** | **Slope** | **VIF** |
| **Panel A: Controls for fundamental industry attributes** | | | | |
| Intercept | 0.4489 | 0.00 | 1.9682*** | 0.00 |
| $BUSSD_{t-1}$ | 0.0969 | 1.26 | 0.1605 | 1.26 |
| $GEOSD_{t-1}$ | 0.1470 | 1.35 | 0.1165 | 1.35 |
| $NONAS_{t-1}$ | 1.1913*** | 1.04 | -1.3920*** | 1.04 |
| $INSTPCS_{t-1}$ | -0.3483** | 1.04 | -2.1129*** | 1.04 |
| $SIZA_{t-1}$ | 0.0649** | 1.24 | -0.1895*** | 1.24 |
| $BIG4_{t-1}$ | -0.1219** | 1.05 | 0.5079* | 1.05 |
| $LEV_{t-1}$ | -0.7849*** | 1.14 | 1.1916*** | 1.14 |
| $HORIZON_t$ | -0.3270*** | 1.27 | 0.3610*** | 1.27 |
| $OBSCIG_t$ | 0.0725*** | 1.34 | -0.0970*** | 1.34 |
| $SHERF_{t-1}$ | -0.5380*** | 1.26 | 2.3049*** | 1.26 |
| $DYNAM_{t-1}$ | -5.4145*** | 1.23 | 7.7484*** | 1.23 |
| $MUNIF_{t-1}$ | -1.1989** | 1.09 | 1.1464** | 1.09 |
| *Adj. Rsq.* | *0.0371* | | *0.0684* | |
| **Panel B: Controls for industry groups (dummies), omits their parameters** | | | | |
| Intercept | 1.1699 | 0.00 | 1.8686 | 0.00 |
| $BUSSD_{t-1}$ | 0.1063 | 1.32 | 0.2156 | 1.32 |
| $GEOSD_{t-1}$ | 0.0573 | 1.62 | 0.1487 | 1.62 |
| $NONAS_{t-1}$ | 0.5960* | 1.10 | -0.9400** | 1.10 |
| $INSTPCS_{t-1}$ | -0.2063** | 1.07 | -2.3319*** | 1.07 |
| $SIZA_{t-1}$ | 0.0710** | 1.36 | -0.1861*** | 1.36 |
| $BIG4_{t-1}$ | -0.1459** | 1.04 | 0.4993* | 1.04 |
| $LEV_{t-1}$ | -0.8198*** | 1.19 | 1.3563*** | 1.19 |
| $HORIZON_t$ | -0.3088*** | 1.28 | 0.3238*** | 1.28 |
| $OBSCIG_t$ | 0.0743*** | 1.34 | -0.0870*** | 1.34 |
| *Adj. Rsq.* | *0.0620* | | *0.0875* | |

*This table reports results for regressions of forecast bias and inaccuracy on fundamentals for operating, investing, financing, and control activities, as well as other determinants. All variables are defined in Table 2. VIF refers to "Variance Inflation Factor", and Adj.Rsq refers to "Adjusted R-Square". The total number of observations (N) equals 3,894 (see Table 1). Significance at 1% or better, 5% or better and 10% or better are denoted by ***, **, and * respectively.*

As discussed in earlier sections, size (SIZA) proxies for litigation risk, forecast frequency (OBSCIG) proxy for frequency of revisions and improvement in information, and forecast horizon (HORIZON) proxies for staleness of information. These are control variables based on prior research (Guo et al., 2011). Thus, big firms are less inclined to mislead or issue erroneous forecasts, so it makes sense that SIZA is positively (negatively) associated with bias (inaccuracy) as per the results. The implication of forecast frequency is similar to that for size, which is consistent with the results. From the table, the longer the forecast horizon, the higher the forecast bias and inaccuracy because forecasts issued earlier would not benefit from recent information.

The industry structure variables are each negatively associated with forecast bias (-1.1989 for MUNIF, -5.4145 for DYNAM, and -0.5380 for SHERF) and positively associated with forecast inaccuracy (1.1464, 7.7484 and 2.3049 for MUNIF, DYNAM and SHERF respectively). This suggests that the industry structure variables are essentially uncertainty indicators. The abundance of sales growth, volatility of sales growth, and concentration in the industry have a positive impact on optimism bias and inaccuracy of the managers' forecasts. Prior research tends to control for industries using dummies, the estimates for which are discarded afterwards because they do not provide any meaning. Here, the slope estimates for specific industry attributes provide a basis for inference. Clearly, the industry structure is external to the firm and accordingly, developments in the external environment tend to be beyond the control of management. This intuition is consistent with the results.

Overall, the results show that managerial forecast errors are due not only to incentive reasons but also to genuine uncertainty on the part of management. The evidence shows that managers, especially of large firms which are the most exposed to litigation costs, cope partly with such costs by issuing pessimistic forecasts. However, managers seem to lack mechanisms to cope with the pressure that factors like the industry structure, institutional holdings, auditors and market participants put on them, for both high expected and realized earnings. This explains why some firms have stopped issuing quantitative forecasts even after increased safe harbor provisions.

## SUMMARY AND CONCLUSION

Prior research has focused largely on the implications of managerial incentives for managerial forecast bias and inaccuracy. This study shows that management forecasts exhibit an optimism bias on average. The bias and inaccuracy are associated with the firm's earnings-relevant factors, disclosure quality and industry attributes, apart from the managerial incentive factors examined by prior research. The safe harbor provisions may be helping some firms to forecast earnings to the public. However, they lack a mechanism to cope with the pressure that market participants put on managers, for both high expected and high realized results. This explains why some firms have stopped issuing quantitative forecasts even after increased safe harbor provisions. Also, some determinants of forecast attributes identified in this study, such as industry concentration, dynamism, and munificence are beyond the control of management. Such factors expose management to a threat of litigation. On the other hand, factors within the firm, such as diversification and leverage are well under management control and should not be the source of management forecast inefficiency. If management is supported to forecast earnings, they would reduce the information asymmetry in the public that is attributable to such internal factors. Our study focused on the bias and accuracy of forecasts because they are readily measurable and constitute the focus of most prior research. We found interesting results as discussed above. Another construct that is often used in connection with forecasts is precision (the converse of dispersion). This is a more difficult construct to use for management forecasts. This is because unlike in the case of analysts' forecasts where several analysts provide forecasts on one firm, based on which dispersion can be assessed, we usually we have one management team issuing forecasts on each firm. However, future research can construct precision based say on the nature and types (e.g. range, qualitative, ceiling or floor) of management forecasts and examine whether the independent variables of this study explain precision. Also, our study is limited to data that is available in FIRSTCALL and so is limited to the USA. This limitation is suffered by all prior research in this area and beyond. Future research can extend our analysis to outside the USA to provide an international perspective on how to improve firms' information environment by encouraging and supporting management to issue earnings guidance and forecasts.

## REFERENCES

Anabila, A. A (2012) "The Proportion of Non-Operating Income, and Analysts' Forecasts," *International Journal of Economics and Finance*, vol. 4(10), p. 15-25

Baginski, S. and Hassell, J (1990) "The market interpretation of management earnings forecasts as a predictor of subsequent financial analysts forecasts revision," *The Accounting Review*, 65(1), p. 175-190

Baginski, S., Conrad E. and Hassell, J (1993) "The effect of management forecast precision on equity pricing and on the assessment of earnings uncertainty," *The Accounting Review*, 68(4), p. 913-927

Baginski, S. P., Hassell, J.M. and Kimbrough, M. D (2002) "The effect of legal environment on voluntary disclosure: Evidence from management earnings forecasts issued in U.S. and Canadian markets." *The Accounting Review*, 77(1), p. 25-50

Behn, B.K., Choi, J. and Kang, T (2008) "Audit Quality and Properties of Analyst Earnings Forecasts," *The Accounting Review*, 83(2), p. 327–349

Bosall.IV., S. B., Bozanic, Z. and Fisher, P (2013) "What Do Management Earnings Forecasts Convey About the Macroeconomy?" *Journal of Accounting Research*, 51(2), p. 225-266

Boyd, B.K (1995) "Ceo duality and firm performance. A contingency model," *Strategic Management Journal,* 16, p. 301–312

Byrnes, N (2003) "Earnings guidance: silence is golden," *Business Week*, New York (May 5), p. 87

Deloitte, (2009) *Earnings Guidance: The current state of play*. Retrieved October 9, 2013 from Web site: www.corpgov.deloitte.com/site/us/

Duru, A. and Reeb, D. M (2002) "International diversification and analysts' forecast accuracy and bias," *The Accounting Review*, 77(2), p. 415-433

Feng, M. and McVay, S (2010) "Analysts' Incentives to Overweight Management Guidance When Revising Their Short-Term Earnings Forecasts," *The Accounting Review*, 85(5), p. 1617-1646

Frankel, R., McNichols, M. and Wilson, P (1995) "Discretionary disclosure and external financing," *The Accounting Review*, 70 (January), p. 135-150

Gong, G., Li L. and Wang, J. J (2011) "Serial Correlation in Management Earnings Forecast Errors," *Journal of Accounting Research*, 49(3), p. 677-720

Hirst, D.E., Koonce, L. and Venkataraman, S (2007) "How Disaggregation Enhances the Credibility of Management Earnings Forecasts," *Journal of Accounting Research*, 45(4), p. 811-837

Irani, A. J (2003) "Management earnings forecast bias and insider trading: comparison of distressed and non-distressed firms," *Journal of Business and Economic Studies,* 9(1), p. 12-25

Jennings, R (1987) "Unsystematic security price movements, management earnings forecasts, and revisions in consensus analysts' forecasts," *Journal of Accounting Research*, 24 (Spring), p. 90-110

Kile, C., Pownall G. and Waymire, G (1998) "How frequently do managers disclose prospective earnings information?" *Journal of Financial Statement Analysis*, 3(3), p. 5-15

Myers, S. C (2001) "Capital structure," *Journal of Economic Perspectives*, 15, p. 81-102

Patell, J. M (1976) "Corporate forecasts of earnings per share and stock price behavior: Empirical tests," *Journal of Accounting Research*, 14(2), p. 246–76

Penman, S. H (1980) "An empirical investigation of the voluntary disclosure of corporate earnings forecasts," *Journal of Accounting Research,* 18(1), p. 132–60

Piotroski, J. D. and Roulstone, D. T (2004) "The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices," *The Accounting Review,* 79(4), p.1119-1151

Pownall, G., Wasley, C. and Waymire, G (1993) "The stock price effects of alternative types of management earnings forecasts," *The Accounting Review*, 68(4), p. 896-912

Rogers, J. L. and Stocken, P. C (2005) "Credibility of Management Forecasts," *The Accounting Review,* 80(4), p. 1233-1260

Thomas, S (2002) "Firm diversification and asymmetric information: evidence from analysts' forecasts and earnings announcements," *Journal of Financial Economics*, 74, p. 373-396

Waymire, G (1985) "Earnings volatility and voluntary management forecast disclosure," *Journal of Accounting Research*, 23(1), p. 268-295

Williams, P.A (1996) "The relation between prior earnings forecast by management and analyst response to current management forecast," *The Accounting Review*, 71(1), p. 103-113

**ACKNOWLEDGMENTS**

This study is based in part on an earlier study originally entitled "Determinants of the Bias, Accuracy and Precision of Management Earning Forecasts". We thank Sharad Asthana of Temple University, and conference participants at the 2005 American Accounting Association Mid-Atlantic Region Annual Meeting, for their invaluable comments on the original study. We are responsible for all errors of this study.

**BIOGRAPHY**

Andrew A. Anabila (PhD in Accounting) is an Assistant Professor of Accounting and Business Law at The University of Texas-Pan American. He can be contacted at: Department of Accounting and Business Law, College of Business Administration, 1201 West University Drive, Edinburg, TX 78539-2999. Phone: 956-665-8084. E-mail: anabilaaa@utpa.edu.

Eunyoung Whang (PhD in Business Administration-Accounting) is an Assistant Professor of Accounting and Business Law at The University of Texas-Pan American. She can be contacted at: Department of Accounting and Business Law, College of Business Administration, 1201 West University Drive, Edinburg, TX 78539-2999. Phone: 956-665-7936. E-mail: whange@utpa.edu.