How Analysts and Whisperers Use Fundamental Accounting Signals To Make Quarterly EPS Forecasts

Susan Machuga[1]
Associate Professor of Accounting
Department of Accounting and Taxation
University of Hartford
West Hartford, Connecticut
Machuga@hartford.edu
(860) 418-9170

Bernard Morzuch
Professor
Department of Resource Economics
University of Massachusetts
Amherst, Massachusetts

Karen Teitel
Associate Professor of Accounting
Department of Economics
College of the Holy Cross
Worcester, Massachusetts

Mahmoud Wahab
Professor of Finance
Department of Economics, Finance & Insurance
University of Hartford
West Hartford, Connecticut

[1] ***Contact author***

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Abstract:
We extend research on fundamental accounting signals (signals) to a quarterly context and investigate the relative efficiency of analysts and whisperers in using signals in generating one-quarter-ahead EPS forecasts. We find (1) a subset of signals found to be relevant in predicting one-year-ahead EPS changes are also relevant in predicting one-quarter-ahead EPS changes, (2) neither analysts nor whisperers fully incorporate information contained in signals in their forecasts, however, whisperers use more signals and (3) the use of signals in predicting one-quarter-ahead EPS changes by analysts and whisperers differs conditional on GDP growth and inflation level. These results support the possibility that whisperers and analysts are different market participants and that whisper forecasts contain unique information. Finally, our findings shed light on how analysts and whisperers develop forecasts of one-quarter-ahead EPS and how they differ from each other. This allows market participants to better use both forecasts when making investment decisions.

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I. INTRODUCTION

The purpose of this paper is to extend research on fundamental accounting signals in three directions. First, we examine whether or not fundamental accounting signals previously found useful for predicting one-**year**-ahead earnings per share (EPS) changes (e.g., Lev and Thiagarajan [1993], Abarbanell and Bushee [1997], and Lambert [2011]) are also useful for predicting one-**quarter**-ahead EPS changes. Second, we compare the relative efficiency with which **w*hisperers*** and ***analysts*** use fundamental accounting signals to generate one-**quarter**-ahead forecasts of EPS changes. To date, no one has looked at the use of fundamental signals by whisperers when making their forecasts of EPS changes; a void this paper aims to fill. Third, we segment the data according to two contextual factors, inflation and economic growth. We then examine how the use of fundamental accounting signals in predicting one-**quarter**-ahead EPS changes differs when conditioned on periods of high and low inflation rates and periods of strong and weak economic growth rates. We also examine the relative efficiency with which whisperers and analysts use fundamental accounting signals to make forecasts of one-**quarter**-ahead EPS changes conditional on these two contextual factors.

Whisper forecasts are relatively new as they date back only to the late 1990s. They represent *unofficial* estimates of next quarter's EPS numbers believed by many to be what investors really think companies will earn. Zack's Investment Research [2013] suggests that whisper forecasts have increasingly become important tools to investors in deciding whether to buy, hold, or sell a stock prior to its quarterly EPS release. In essence, companies are now facing two hurdles which they must overcome in order to receive a favorable stock price reaction in the market upon release of their EPS numbers: the first hurdle is they must exceed analysts' forecast,

while the second, and perhaps even more important hurdle, is they must exceed whisperers' forecast. For example, Facebook Corporation beat analysts' EPS forecast for the fourth quarter of 2012, but failed to beat the whisper number, which resulted in a decline in their stock price **(**Krantz [2013]**),** thereby supporting the proposition that whisper numbers have become another benchmark that is carefully watched by investors during the earnings-reporting season along with analysts' numbers.

The data sample used in this study consists of: (a) quarterly whisperers' EPS forecasts (which we manually collect from Whispernumber.com website), (b) quarterly analysts' EPS forecasts (which we download from the Institutional Brokers Estimates System database - IBES), (c) quarterly fundamental accounting variables (which we download from COMPUSTAT database), and (d) quarterly macroeconomic data (which we download from globalfinancialdata.com website). The final sample consists of 66 firms with 219 forecasts of quarterly EPS for the time period 2010-2011.

Our results indicate that a subset of the fundamental accounting signals found to be useful in Lev and Thiagarajan [1993], Abarbanell and Bushee [1997] and Lambert [2011] for predicting one-**year**-ahead EPS changes are also relevant in a quarterly setting. In addition to the importance of current-quarter's EPS changes for forecasting one-**quarter**-ahead EPS changes, fundamental accounting signals relating to sales (such as gross profit, change in mark-up, accounts receivable, and inventory) are statistically significant, and explain over 70% of the variability of one-**quarter**-ahead EPS changes. When examining the use of these fundamental accounting signals by both analysts and whisperers, we find that they use different fundamental accounting signals when predicting one-**quarter-**ahead EPS changes. Analysts use accounts receivable, free cash flow, and change in the firm's cash position, while whisperers use current-

quarter's EPS changes, accounts receivable, capital expenditures, and free cash flow when forecasting one-**quarter**-ahead EPS changes. In addition, both analysts and whisperers do not fully incorporate information contained in fundamental accounting signals when making their forecasts; however, the model for whisperers possesses higher explanatory power than that for analysts (14% versus 9%, respectively). It is also noteworthy that whisperers are better at embedding information regarding reversals of quarterly EPS changes into their forecasts of next-quarter's EPS changes than do analysts. This finding may explain the continued and increasing interest in whisperers' forecasts of EPS as a complement to analysts' forecasts of EPS. While the fundamental accounting signals that are used by both analysts and whisperers are somewhat similar, whisperers seem to use more signals than do analysts when making their forecasts of one-**quarter**-ahead EPS changes, which raises the possibility that whisperers may be different from analysts.

We also investigate the role that two macroeconomic factors (quarterly growth rates of U.S. Gross Domestic Product - GDP, and quarterly U.S. Inflation Rates computed by chain-linking monthly inflation rates using the Consumer Price Index - CPI) play in affecting one-**quarter**-ahead EPS forecasts made by whisperers and analysts. We find for periods of low inflation and periods of high GDP growth, in isolation, as well as in combination, both analysts' and whisperers' use fundamental accounting signals in making forecasts of next-quarter's EPS changes. Whisperers, however, have a better understanding than analysts regarding the importance of different fundamental signals for making forecasts of one-**quarter**-ahead EPS changes as evidenced by the higher explanatory power (adjusted R^2) of the conditional forecast model for whisperers relative to that of analysts. Whisperers use cash, change in mark-up and gross margin in their one-**quarter**-ahead EPS predictions during periods of low inflation, and use

capital expenditure as an additional variable when making their predictions during periods of high GDP growth, while analysts do not. This is consistent with whisperers, perhaps, possessing a better understanding than analysts of how the macro environment impacts one-**quarter**-ahead EPS changes.

II. LITERATURE REVIEW

The use of fundamental signals in predicting EPS changes and abnormal stock returns appears to be an area of research of interest in recent years to both academics (e.g., Richardson et al. [2010] and Lambert [2011]) and the news media (e.g., Bloomberg and CNBC TV channels). In principle, fundamental signals include not only information found in published corporate financial statements but also information about a firm's product markets, competitors, and the overall macro-economy. The original fundamental signals thought to be useful in explaining EPS changes were constructed based on information in Accounting Concepts Statement #8 issued by the Financial Accounting Standards Board (FASB [2010]). This statement suggests that data from financial statements should be useful for EPS forecasts since these statements are the "accrual" equivalent of "cash-basis" accounting statements. FASB refers to the different financial statement accounts (and their associated dollar amounts), which appear on reported financial statements, as "items". Ou and Penman [1989] refer to changes in balance sheet and income statement items, examined in relation to each other, as "fundamental signals".

Ou and Penman [1989] identify 68 data-driven accounting and financial signals. They then narrow down those signals to 16 using statistical search algorithms, and rank the signals from highest to lowest in terms of their marginal contribution to explaining

variability in *annual* EPS. Lev and Thiagarajan [1993] select 12 fundamental signals which they claim are used by practicing financial analysts to predict annual excess stock returns (i.e., abnormal stock returns). Abarbanell and Bushee [1997] use those same 12 fundamental signals to predict one-**year**-ahead EPS changes. Lambert [2011] builds upon the fundamental signals developed by Abarbanell and Bushee [1997]. Lambert [2011] uses nine of Abarbanell and Bushee's [1997] fundamental signals and adds additional fundamental signals intended to proxy for operating leverage, market share, sales price markup over cost, and total manufacturing costs. Lambert's [2011] additional fundamental signals are based on guidance from both financial and managerial accounting concepts: (i) stated in FASB concepts statements, and (ii) included in accounting textbooks used to teach financial statement analysis. He includes fundamental signals that are expected to be useful for predicting future EPS changes, but were not included in previous fundamental studies since they were not cited by analysts as being useful variables. Lambert's [2011] results suggest that the additional fundamental signals used do provide significant incremental explanatory/predictive power over those used in Abarbanell and Bushee [1997] however are not efficiently used by analysts. These findings suggest that there may be additional fundamental signals useful in predicting EPS changes that are not efficiently used by analysts, but may be used by other investors (e.g., whisperers).

In this paper we examine the use of fundamental signals in predicting EPS changes. Abarbanell and Bushee [1997] state that "predicting accounting earnings, as opposed to explaining stock returns, should be the main task of fundamental analysis". We agree with this statement since fundamental signals are based on reported accounting

information and therefore should be useful for predicting future earnings, which is in line with the conceptual framework and accounting concepts statements issued by the FASB. Indeed, the primary job of analysts employed by Wall Street firms is to predict EPS, and not necessarily to predict stock prices or stock returns.

One objective of our paper is to determine whether or not the same fundamental signals useful for predicting *annual* EPS changes are also useful when predicting *quarterly* EPS changes. An equally important and interesting issue is whether or not both analysts and whisperers use the same fundamental signals when making forecasts of one-**quarter**-ahead EPS changes. These issues are important for understanding the composition of each information set used by each group (analysts versus whisperers) in forecasting their one-**quarter**-ahead changes in EPS.

It is widely accepted that the source of whisper forecasts is unknown due to their anonymity which is preserved when they "whisper". Whisperers are individuals who may be security analysts, managements, or individual investors who post anonymously on popular internet websites (e.g., whisperanalysts.com and whispernumber.com). Given whisper forecasts are increasing in number in terms of company-coverage and over time and they are frequently cited in the financial media as being important benchmarks, knowing more about how whisper forecasts are developed should be of interest to many investors. More specifically, which fundamental signals are common and which are different across the two groups (analysts and whisperers) may help shed some light on similarities and differences in the makeup of their forecasts.

The news media (e.g., CNBC and Bloomberg TV) regularly refer to whisperers' and analysts' EPS forecasts during the earnings season. These media also seem to be

continually contrasting whether a company's reported EPS number has beaten analysts' as well as whisperers' forecast of EPS or just the analysts' forecast of EPS. Furthermore, the stock price reaction to a company's earnings' release seems to be affected as well by this comparison and contrast between analysts' and whisperers' EPS forecasts (e.g., Bagnoli, et al [1999] and Nawrocki [2012]).

Wall Street firms employ financial analysts who specialize in an industry or a group of stocks within an industry. They are responsible for generating earnings' forecasts which generally tend to be conservative and easy to beat in order not to disappoint investors when issuing a "buy" recommendation. By undershooting and providing conservative EPS forecasts, analysts hope for a favorable stock price reaction upon the release of the EPS number, which in all likelihood should at least meet if not beat their EPS forecast. If their forecast is too high, however, and they have issued a "buy" recommendation at a time when management reports a lower EPS number than the analysts' forecast, the stock price drops and both the firm and the analyst lose some credibility on the street. Zack's Investment Research [2013] finds that using whisper forecasts along with analysts' forecasts in a "secret formula" allows them to better identify stocks that are more likely to beat earnings by a wide margin than just using analysts' forecasts alone. Hence, whisperers' forecasts serve to complement analysts' forecasts, and also reduce forecast errors rather than relying solely on analysts' forecasts.

Accordingly, we start with a regression model which associates next quarter's EPS changes with current-quarter's EPS changes in addition to a number of fundamental signals. We then examine whether or not analysts' and whisper forecasts use the same set of fundamental signals in making their forecasts of one-**quarter**-ahead EPS changes.

Lastly, we examine the associations between analysts' and whisperers' forecast errors and the fundamental signals. This is important because if forecast errors contain information that is not fully utilized by either group when making their conditional forecasts of EPS changes (i.e., forecast errors are associated with fundamental signals), it suggests that either group is not making full and efficient use of all publicly available information when making their forecasts and therefore their forecasts can be improved upon with judicious use of additional fundamental information.

III. DATA AND SAMPLE SELECTION:

Our data consist of whisper forecasts of EPS manually collected from whispernumber.com website beginning with the second quarter of 2010 and ending with the second quarter of 2011. We collected whisper forecasts for 125 randomly selected firms from the Standard and Poor's 500 Index (S&P500). After combining this data with IBES, we end up with a sample of 364 firm-quarter observations from 102 firms. We use the mean of analysts' forecasts on the last day prior to the earnings announcement date (Brown and Caylor [2005]) as whisperers tend to wait till a day or two before the earnings are announced to post their forecasts. This eliminates any timing advantages towards whispers by using a more current analyst quarterly mean which does not contain stale forecast. If anything, our results are biased against whispers, and in favor of analysts, as whisperer' forecasts are posted a day or two earlier or on the same day as analysts' forecasts. Downloading fundamental signals (variables) from COMPUSTAT database reduced the sample to 219 firm-quarter observations for 66 firms over 5 quarters.

IV. MODEL DEVELOPMENT:

Due to the reversal nature of current accruals, prior research has consistently shown that next-year's changes in EPS are negatively associated with current-year's changes in EPS

(Defond & Park [2001], Pae [2005] and Chan et al. [2004]). In addition to the yearly nature of this relationship, we also expect reversals in changes of EPS to be present on a quarterly basis due to the short-term nature of many accruals. Therefore, we begin with a model that specifies one-**quarter**-ahead EPS changes as a function of current-quarter's EPS changes plus a random disturbance term, as follows:

$$(EPS_{i,q+1} - EPS_{i,q})/P_{i,q} = \alpha + \beta\,(EPS_{i,q} - EPS_{i,q-1})/P_{i,q-1} + \mu_{i,q} \qquad (1)$$

where:

$EPS_{i,q+1}$ = earnings-per-share for company *i* in quarter *q+1*

$EPS_{i,q}$ = earnings-per-share for company *i* in quarter *q*

$EPS_{i,q-1}$ = earnings-per-share for company *i* in quarter *q-1*

$P_{i,q}$ = stock price for company *i* in quarter *q*

$P_{i,q-1}$ = stock price for company *i* in quarter *q-1*

and α and β are parameters to be estimated. If earnings exhibit a reversal behavior from quarter-to-quarter, the expected sign of the slope coefficient, β, in Model (1) is negative and statistically significant at conventional levels. The assumptions about the error term $\mu_{i,q}$ are that it has zero expected value, constant variance, and zero covariance across firms and over time. We test for constant variance, but cannot test for autocorrelation of the error term over time because of the limited time-series per firm.

In previous studies, fundamental accounting signals along with current-year's EPS changes have been used to predict one-**year**-ahead *annual* EPS changes. Abarbanell and Bushee [1997], for example, are considered one of the "foundation" articles in the fundamental analysis literature that investigates the usefulness of fundamental signals for predicting *annual* EPS

changes. We apply a similar approach to model one-**quarter**-ahead EPS changes using *quarterly* measures of the fundamental signals and current-quarter EPS changes.

Most financial statement analysis textbooks emphasize the importance of assessing the quality of reported earnings when making earnings predictions. Fundamental signals (i.e., changes in linear combinations of balance sheet and income statement items) are argued to be useful for assessing persistence of earnings growth. Hence, analysts and investors alike should focus not only on the bottom line EPS number, but should also make use of components of income statement and the balance sheet items in order to assess the degree of persistence of EPS, which permits more accurate predictions of one-**year**-ahead EPS changes.

We begin with the original 12 fundamental signals chosen by Lev and Thiagarajan [1993] which have been outlined by security analysts as being important to them in forming their EPS forecasts, and the resultant buy/hold/sell recommendations issued to investors. These 12 fundamental signals are: inventory, accounts receivable, capital expenditures, R&D expenses, gross margin, selling and administrative expenses, provision for doubtful receivables, effective tax rate, order backlog, labor force, LIFO indicator and audit qualification (page 193). Lev and Thiagarajan [1993] investigate two main questions: (a) whether the set of 12 fundamental signals repeatedly referred to in analysts' reports as well as in financial statement analysis textbooks is actually used by analysts along with current-year's EPS changes when forming their one-**year**-ahead EPS changes, and (b) whether or not this set of 12 fundamental signals adds incremental information beyond that conveyed by current-year's EPS changes when associating them with excess stock returns.

To increase their sample size, Lev and Thiagarajan [1993] remove three of the original 12 fundamental signals: provision for doubtful receivables, order backlog, and R&D expenses, as

these three items are often not reported for most firms. In addition to eliminating those three variables, we also eliminate three additional variables: audit qualification, labor force, and LIFO indicator as this information is not available on a *quarterly* basis in COMPUSTAT database, thereby leaving a total of six fundamental signals.

Our second model is a regression of the one-**quarter**-ahead EPS changes on current-quarter's EPS changes in addition to the six fundamental signals, as follows:

$$(EPS_{i,q+1} - EPS_{i,q})/P_{i,q} = \alpha + \beta_1 (EPS_{i,q} - EPS_{i,q-1})/P_{i,q-1} + \beta_2 (INV_{i,q}) + \beta_3 (AR_{i,q}) + \beta_4 (CAPX_{i,q}) + \beta_5 (GM_{i,q}) + \beta_6 (S\&A_{i,q}) + \beta_7 (ETR_{i,q}) + \omega_{i,t} \quad (2)$$

where the top line in Model (2) is a repeat of the dependent variable and independent variable presented in Model (1). Furthermore:

$INV_{i,q}$ = percent change in inventory – percent change in sales for company *i* in quarter *q;*

$AR_{i,q}$ = percent change in accounts receivable – percent change in sales for company *i* in quarter *q;*

$CAPX_{i,q}$ = percent change in an industry's capital expenditures – percent change in capital expenditures for company *i* in quarter *q;*

$GM_{i,q}$ = percent change in sales – percent change in gross margin for company *i* in quarter *q;*

$S\&A_{i,q}$ = percent change in selling, general and administrative expenses – percent change in sales for company *i* in quarter *q;*

$ETR_{i,q}$ = (average tax rate for the prior three quarters – the tax rate for the current quarter) * the change in EPS for the current year for company *i* in quarter *q;*

and α and β_1 through β_7 are parameters to be estimated. The error term $\omega_{i,t}$ is treated similarly as $\mu_{i,q}$ in Model (1). The remaining variables are calculated as quarterly percent changes computed in relation to the mean from the prior two quarters. They capture negative (or bad news)

information about future EPS changes, and due to the expected reversal nature of EPS changes, we expect signs of the Beta coefficients in Model (2) to be negative.

Lambert (2011) chose additional variables often found in both Financial Accounting and Managerial Accounting textbooks to be important fundamental signals for predicting future *annual* EPS changes. These additional fundamental signals are intended to proxy for operating leverage, market share, sales price markup over cost, and total manufacturing costs. Our third model is designed to examine whether the additional fifteen fundamental signals used in Lambert (2011) to predict one-**year**-ahead EPS changes are also useful for predicting one-**quarter**-ahead EPS changes. We eliminated from our model three of the fifteen fundamental signals as they are relevant for manufacturing firms only, which is too restrictive given the composition of firms used in this study.

Our third model is a regression of the one-**quarter**-ahead EPS changes on: (a) current-quarter's EPS changes, (b) the six fundamental signals used in Model (2), and (c) the additional 12 fundamental signals introduced in Lambert [2011]. More formally, Model (3) is:

$$
\begin{aligned}
(EPS_{i,q+1} - EPS_{i,q})/P_{i,q} = {} & \alpha + \beta_1 (EPS_{i,q} - EPS_{i,q-1})/P_{i,q-1} + \\
& \beta_2 (INV_{i,q}) + \beta_3 (AR_{i,q}) + \beta_4 (CAPX_{i,q}) + \\
& \beta_5 (GM_{i,q}) + \beta_6 (S\&A_{i,q}) + \beta_7 (ETR_{i,q}) + \\
& \beta_8 (MKTSHR_{i,q}) + \beta_9 (CHG\_MKTSHR_{i,q}) + \beta_{10} (MU_{i,q}) + \\
& \beta_{11} (CHG\_MU_{i,q}) + \beta_{12} (FCF_{i,q}) + \beta_{13} (CHG\_FCF_{i,q}) + \\
& \beta_{14} (CASH_{i,q}) + \beta_{15} (CHG\_CASH_{i,q}) + \beta_{16} (DEBT\_AT_{i,q}) + \\
& \beta_{17} (CHG\_DEBT\_AT_{i,q}) + \beta_{18} (DISC\_INC_{i,q}) + \\
& \beta_{19} (OP\_LEV_{i,q}) + \eta_{i,q} \qquad (3)
\end{aligned}
$$

where the top three lines in Model (3) are a repeat of the dependent variable and independent variables presented in Model (2). Furthermore:

$MKTSHR_{i,q}$ = sales/sales of all firms in the same 4-digit SIC code industry for company *i* in quarter *q;*

$CHG\_MKTSHR_{i,q}$ = percent change in MKTSHR for company *i* in quarter *q;*

$MU_{i,q}$ = (sales – cost of goods sold)/cost of goods sold for company *i* in quarter *q;*

$CHG\_MU_{i,q}$ = percentage change in MU for company *i* in quarter *q;*

$FCF_{i,q}$ = free cash flow defined as (operating cash flows – capital expenditures – dividends)/total assets for company *i* in quarter *q;*

$CHG\_FCF_{i,q}$ = percentage change in FCF for company *i* in quarter *q;*

$CASH_{i,q}$ = cash/total assets for company *i* in quarter *q;*

$CHG\_CASH_{i,q}$ = percent change in CASH for company *i* in quarter *q;*

$DEBT\_AT_{i,q}$ = total liabilities/total assets for company *i* in quarter *q;*

$CHG\_DEBT\_AT_{i,q}$ = percent change in DEBT_AT for company *i* in quarter *q;*

$DISC\_INC_{i,q}$ =discretionary income defined as (sales – cost of goods sold – depreciation – taxes –dividends)/sales for company *i* in quarter *q;*

$OP\_LEV_{i,q}$ = operating leverage defined as (income before extraordinary items + selling and administrative expenses + depreciation)/income before extraordinary items for company *i* in quarter *q;*

and α and β_1 through β_{19} are parameters to be estimated. The error term, $\eta_{i,q}$, is treated similarly as $\mu_{i,q}$ in Model (1).

Abarbanell and Bushee [1997] compare the associations between: (a) fundamental signals and future *annual* EPS changes, (b) fundamental signals and analysts' *annual* EPS forecast revisions, and (c) fundamental signals and analysts' *annual* forecast errors, to examine the extent to which information contained in fundamental signals about future earnings is fully exploited by analysts in forming their EPS forecasts. They do so by running eight cross-sectional regressions, one for each year 1983 to 1990, inclusive, and testing whether the mean of the eight cross-

sectional coefficient estimates is significant based upon the standard error of the eight annual cross-sectional coefficient estimates. Abarbanell and Bushee [1997] conclude that analysts are aware of the association of some fundamental signals with future *annual* EPS changes and embed this information in their *annual* EPS forecast revisions and forecasts. However, analysts seem to underreact to some of the fundamental signals as the sign on the fundamental signals' coefficients estimate is the same when the forecast error is the dependent variable as it is when the forecast revision is the dependent variable. These findings suggest that even though analysts use fundamental signals in revising their earnings forecasts, they do not use detailed information pertaining to fundamental signals as efficiently as they should. We test whether this is also true with *quarterly* data and whether or not this is also true for analysts and whisperers, two issues not previously addressed in the accounting literature.

To isolate the impact of the use of information contained in the fundamental signals by analysts/whisperers, we re-estimate Models (1), (2) and (3), presented above, using analysts' predictions of one-**quarter**-ahead EPS changes $(AF_{i,q+1} - EPS_{i,q})/P_{i,q}$ as the dependent variable, then using whisperers' predictions of one-**quarter**-ahead EPS changes $(WF_{i,q+1} - EPS_{i,q})/P_{i,q}$ as the dependent variable. We also include current-quarter's EPS changes along with the fundamental signals, as previous research indicates analysts' forecast errors are associated with prior-year EPS changes (Abarbanell and Bushee [1997], Ali et al. [199], DeBondt and Thaler [1990]).

We use forecasts of EPS changes rather than forecast revisions in our models in an attempt to address perceived timing advantages of whisperers. Unlike analysts', who begin forecasting at the beginning of the quarter, whisperers do not whisper and post their forecasts until closer to the end of the quarter. Therefore, to determine how efficiently analysts use

fundamental signals, we measure the difference between the mean of analysts' forecasts of next-quarter's EPS on the last day prior to the earnings announcement date (Brown and Caylor [2005]) and current-quarter's reported EPS. For whisperers, we measure the difference between the mean of all whisper forecasts of next-quarter EPS prior to the earnings announcement date and current-quarter's reported EPS. If fundamental signals are used efficiently, both analysts and whisperers should adjust their forecast of next-quarter's EPS from the current-quarter's EPS based on the estimated associations found in Models (1), (2), and (3) which measure the connection between the fundamental signals and next-quarters EPS changes.

Finally, we examine the association between analysts'/whisperers' forecast errors and the fundamental signals. We do so by re-estimating Models (1), (2) and (3), presented above, using analysts' forecast errors $(AF_{i,q+1} - EPS_{i,q+1})/P_{i,q}$ as the dependent variable, then using whisperers' forecast errors $(WF_{i,q+1} - EPS_{i,q+1})/P_{i,q}$ as the dependent variable. If the forecast errors of either analysts or whisperers are associated with fundamental signals, it suggests that either group may be underreacting or overreacting to the signals depending on the signs of coefficients' estimates related to fundamental signal as compared to their corresponding signs from the regression that uses forecasts of one-**quarter**-ahead EPS changes as the dependent variable, as stated above.

V. EMPIRICAL RESULTS:

Table (1) provides definitions for all of our variables. Table (2) presents summary descriptive statistics for variables used in our models. The presence of the reversing nature of current accruals is confirmed by the fact that the mean of one-**quarter**-head EPS changes is negative yet the mean of current-quarter EPS changes is positive. The mean forecasted EPS change by analysts (whisperers) is -0.0003 (-0.0000) indicating, on average, analysts' forecast a lower EPS in the current quarter than last quarter's EPS. Conversely, on average, whisperers do not forecast changes in EPS over two consecutive quarters.

Prediction of one-quarter-ahead EPS changes by both analysts and whispers

Our first model is based on the reversal nature of current accruals which causes a negative association between current and lagged annual EPS changes (Defond & Park [2001], Pae [2005], and Chan et al. [2004]) Due to the short-term nature of many of the accruals, we expect this reversal also to be present on a *quarterly* basis. This would be consistent with previously documented evidence which used *annual* data. Results reported in column 1 of Table 3 confirm that *quarterly* EPS changes exhibit the same reversal pattern found for *annual* data, and that the estimated β coefficient has a negative sign and is statistically significant (coefficient= - 0.0327, p-value < 0.0001).

The second model presents evidence regarding the incremental contribution of the six fundamental signals (along with current-quarter's EPS change) introduced by Lev and Thiagarajan [1993], measured in their study on an *annual* basis and used by Abarbanell and Bushee [1997] to predict one-**year**-ahead EPS changes. Our results using *quarterly* data are reported in column 2 of Table 3. We find that three of the six fundamental signals (INV, AR and GM) have incremental value, in addition to current EPS changes, for predicting next quarter's EPS changes. Therefore, those signals appear to be used by investors to assess the persistence of future earnings.

From column 2 of Table 3, the fundamental signal with the largest statistically significant coefficient is GM, which is not surprising in light of the news media's focus on not only whether or not a company's reported EPS number meets or beats analysts' EPS forecast, but also whether or not a company's reported sales revenue number meets or beats analysts' top line sales revenue forecast, which has implications for the GM fundamental signal. It is worth mentioning also that the other two statistically significant signals (INV and AR) relate directly to the GM fundamental

signal. Accounts receivable (AR) and sales revenue should be associated as changes in sales volume result in changes in AR. Likewise, inventory (INV), and cost of goods sold, should be highly associated with sales as growth in inventory and/or cost of goods sold depends on current and future sales expectations.

Previous research assumes that fundamental variables are negatively associated with future EPS changes. This appears to be true for inventory as an increase in inventory above the level required to support future sales projections should be regarded as bad news for future EPS. In contrast, an increase in receivables that is higher than expected given future sales projections may be due to a change in the firm's credit policy, or due to firms arranging financing of receivables through their own financing subsidiaries so as to make it easier for customers to purchase items on credit. Lastly, a change in sales that is greater than the change in gross margin should be construed as a positive signal for future earnings, in that sales increases will eventually lead to price increases and higher gross profit margins based on higher demand relative to potential supply, which should translate into future gross profit margin increases.

Abarbanell and Bushee's [1997] results indicate that the coefficients on prior-year EPS changes and the effective tax rate are significantly negative in seven of the eight annual cross-sectional regression models. However, these results may be unreliable due to potential cross-correlations among observations within each year of their eight-year study period. To address this possibility, they compute means of estimated coefficients on each of the fundamental signals and test for statistical significance of means of annual coefficients using the estimated standard errors of the yearly coefficient estimates. Their mean results computed from multiyear coefficients suggest that: (a) reversals in EPS changes are statistically significant and have a negative coefficient, (b) accounts receivable and capital expenditure are statistically significant

and have a positive coefficient, and (c) inventory, gross profit, income tax rate, earnings quality, and labor force are statistically significant and have a negative coefficient.

When Abarbanell and Bushee [1997] include only EPS changes as an independent variable, their adjusted R^2 is 7%. When they include fundamental accounting signals in the regression along with EPS changes, their adjusted R^2 increases to 16%. Our results using *quarterl*y data shown in Table 3 columns 1 and 2, show an adjusted R^2 that increases from 26% when using only EPS changes to 69% when using the six fundamental signals along with EPS changes. Thus, our models estimated with quarterly data exhibit a better fit even though quarterly data may contain more noise than smoothed annual data.

Our third model includes an additional 12 variables of the 15 fundamental signals used by Lambert [2011]. These are intended to proxy for operating leverage, market share, and sales price markup over cost. They are included along with the six fundamental signals used in Model (2). We are interested in examining the marginal contribution of those 12 additional variables to the explanatory power of Model (2) which includes only EPS changes and six fundamental variables. Estimation results for Model (3) are presented in column 3 of Table 3. Only one of the twelve additional variables has a statistically significant coefficient, namely, the CHG_MU variable, which again is related to sales and cost of goods sold (or gross margin). Note that in Model (2) we found GM to be statistically significant. This is not surprising as both GM and CHG_MU are based on changes in sales relative to cost of goods sold. The coefficient estimates on GM, INV and EPS changes remain statistically significant even in the presence of the additional 12 fundamental signals. Regarding the contribution of the 12 additional variables to the fit of the model, our results indicate the adjusted R^2 for Model (2) is 69%, and for Model (3)

is 70%, so that collectively, the twelve additional variables contribute very little (if any) to Model (3)'s explanatory power.

The next step is to determine the extent to which analysts and whisperers incorporate fundamental signals into forecasts of one-**quarter-**ahead EPS changes. This is accomplished by redefining the dependent variable in Models (1), (2) and (3) to reflect analysts' forecasts of EPS changes (columns 4, 5, and 6 in Table 3), and whisperers' forecasts of EPS changes (columns 7, 8 and 9 in Table 3). First, as to analysts' forecasts of EPS changes, column 4 shows that the negative association with current EPS changes is still present and statistically significant. However, when the six fundamental signals are included in column 5 (i.e., Model (2)), the negative association is no longer significant. The only fundamental signal that is significant is AR. When the additional 12 fundamental signals are introduced in column 6 (i.e. Model (3)), the positive association with AR is no longer significant. However, FCF and CHG_CASH are negative and significant. The interpretation is that, on a quarterly basis, analysts underestimate the earnings reversal and focus instead on cash flows when developing forecasts of EPS changes.

Whisperers' forecasts of EPS changes are analyzed in columns 7, 8 and 9 in Table 3. In all estimations, the coefficient on current EPS changes is statistically significant. When the six fundamental signals are added in column 8 (i.e., Model (2)), only AR has a statistically significant impact on forecasted EPS changes. In column 9 (i.e., Model (3)), with the addition of the 12 fundament signals, AR loses its significance but CAPEX has a positive and statistically significant impact, while FCF has a negative and statistically significant impact. Consistent with analysts' forecasts, whisperers focus on cash flows when estimating quarterly EPS changes. However, whisperers embed the earnings reversal tendencies into their forecasts while analysts do not.

Using *annual* data, Abarbanell and Bushee [1997] find current EPS changes, gross profit, tax rate, and labor force are all negatively associated with one-**year**-ahead forecast revisions. This is consistent with the negative associations these fundamental signals have with one-**year**-ahead EPS changes. Our results indicate that neither analysts nor whisperers are incorporating into their forecasts of EPS changes as many or the same fundamental signals that are associated with one-**quarter**-ahead EPS changes. However, it appears that whisperers at least incorporate earnings reversals into their EPS forecasts while analysts do not.

Diagnostic tests

At this stage, it is important to address the diagnostic tests that we conducted relating to the three models for EPS changes, the three models for analysts' forecasts of EPS changes, and the three models for whisperers' forecasts of EPS changes. Again, the estimation results themselves are presented in Columns 1-9 of Table 3. For any set of three models, there are two general diagnostic issues that we address: (1) the behavior of the estimated residuals and (2) the behavior of the independent (i.e., regressor) variables among themselves. Specific problems that relate to the first issue are non-constant variance (i.e., heteroscedasticity) and abnormalities due to residuals that may appear as outliers. Regarding the second issue, the pertinent problem is the possibility of collinearity among the regressors (i.e., multicollonearity). Also with regard to addressing the residuals, we are unable to assess the possibility of correlation of the residuals over time (i.e., autocorrelation) because of the limited time-series for each firm. Lastly, we do not worry about contemporaneous correlation between any individual regressor and the disturbance term (which can lead to biased and inconsistent regression coefficient estimates) because all regressors are lagged; i.e., there is no contemporaneous correlation between a regressor and the residual.

More specifically, for each regression, we plotted the residuals against fitted values of the dependent variable and against each regressor. We observed no pattern in the size of the estimated residuals as any of the regressor variables or the fitted dependent variable changed in size. Formally, we conducted White's test for heteroscedasticity (White [1980]). In all of the estimations except one (to be addressed below), we failed to reject the null hypothesis of homoscedastic errors (i.e., constant variance). In addition, the plot of the residuals for each of the estimations had a symmetrical (and in some cases, a bell-shaped) appearance. Importantly, there was a noticeable absence of outlier-estimated residuals for each of the plots.

When it came to assessing the possibility of collinearity among the regressor variables for each of the nine regressions, we used two approaches. For each regression, we calculated the variance inflation factor (VIF) for each variable. Uniformly and across all specifications, VIFs were 1.9 or less, suggesting absence of multicollinearity. The rigorous approach for assessing collinearity is to calculate the eigenvalues for all regressors and their condition indices (Belsley, et al [1980]). This approach confirmed the absence of collinearity as well. Had we concluded that collinearity or heteroscedasticity or both were present, we would have had to be concerned about the standard errors of the regression coefficients that are reported in Table 3. Problems with standard errors ultimately lead to problems with our tests. As such, our diagnostic tests reveal that our estimation results are reliable.

Lastly, the version of White's test that we used is a joint test for homscedasticity and correct model specification as the null hypothesis (White [1980], p. 823). The alternative hypothesis is that we have either heterocedasticity or model misspecification or both. When we estimated Model (2) for analysts' forecasts of EPS changes, we had strong evidence to reject the null hypothesis. When we moved to the fuller specification, Model (3) for analysts' forecasts of EPS

changes, White's test revealed that we were far from being able to reject the null hypothesis. Thus, test results suggest that inclusion of additional variables supported our model specification.

Comparison of analysts' and whisperers' forecast errors of one-quarter-ahead EPS changes

The last step is to rerun the three models using analyst forecast errors or whisper forecast errors as the dependent variable. These equations allow us to determine if inefficiencies present in either forecast are due to under- or over-reaction to fundamental signals. The results for analysts' forecasts are presented in Table 4. Columns 1, 2 and 3 are estimation results from Table 3 columns 4, 5 and 6 using analysts' forecasts of EPS changes as the dependent variable, while columns 4, 5 and 6 in Table 4 use analyst forecast errors as the dependent variable. Columns 2 and 3 of Table 4 demonstrate that analysts are not efficiently incorporating reversals in EPS changes into their estimates. If they were, the coefficients on quarterly EPS changes in columns 2 and 3 of Table 4 would be statistically significant, however this is not the case. Observing the statistically significant coefficients on quarterly EPS changes in columns 4, 5 and 6 in Table 4, we conclude that current EPS changes is a statistically significant variable for explaining variability in analysts' forecast errors, supporting the notion that analysts are not efficiently incorporating the reversal tendency in EPS changes into their estimates. Applying the same reasoning, S&A and DEBT_AT are also not fully embedded into analysts' forecasts of quarterly EPS changes (see coefficients in columns 2 and 3 compared to columns 5 and 6 in Table 4). The S&A explanation is consistent with the focus on cash flows found in prior analyses. The significance of DEBT_AT implies that risk is not being adequately embedded in analysts' forecasts of EPS changes.

Whisper forecast errors are presented in Table 5. Columns 1, 2 and 3 are the estimation results from Table 3 columns 7, 8 and 9 using whisperers' forecasts of EPS changes as the

dependent variable, while columns 4, 5 and 6 in Table 5 use whisper forecast errors as the dependent variable. While whisperers appear to embed earnings reversals in their forecasts of quarterly EPS changes (see columns 1, 2 and 3 in Table 5), they are still underreacting and are not efficiently capturing all the information included in current EPS change (see columns 4, 5 and 6 in Table 5) due to their association with whisperers' forecast errors. The only other fundamental signal that whisperers are underreacting to is DEBT_AT which is statistically significant.

In summary, the results in Table 3 indicate that fundamental signals are useful in predicting one-**quarter**-ahead EPS changes after controlling for current quarter's EPS changes. However, only a subset of the fundamental signals that focus on sales, gross margin, cash flows and the related balance sheet accounts of inventory and accounts receivable are most relevant in predicting one-**quarter**-ahead EPS changes. Analysts not only underreact to the fundamental signals in estimating quarterly earnings, but they do not incorporate current-period EPS reversals attributed to current accruals that is documented in prior research (Defond & Park [2001], Pae [2005] and Chan et al. [2004]). Whisperers do a better job at embedding information in current EPS changes, but they too underreact to this information and fundamental signals. The smaller number of fundamental signals found to be significant in our quarterly analyses results compared to annual earnings results in Lev and Thiagarajan [1993], Abarbanell and Bushee [1997] and Lambert [2011] may be a result of our small sample size, different time periods analyzed, conditional settings or more variability in quarterly data.

VI. ADDITIONAL ANALYSES

Both reviews of existing research of fundamental analysis by Bauman [1996] and Richardson et al [2010] note that an important area for future academic research, which has

currently been investigated to a limited extent, is how contextual factors may interact with fundamental signals in their prediction of future EPS changes. Lev and Thiagarajan [1993] perform analyses conditional on three economic variables (annual changes in the consumer price index (CPI), gross national product (GNP), and level of business inventories). In high growth environments with low inflation, they find that growth in receivables and inventory is good news and a positive fundamental signal for future *annual* EPS changes. We extend their results using *quarterly* data on whisper and analysts' forecasts of EPS changes using both inflation and gross domestic product.

We collect data on U.S. quarterly Consumer Price Index (CPI) as well as quarterly real U.S. Gross Domestic Product (GDP). These two contextual factors can be thought of as capturing business cycle effects on business sector activity and corporate earnings. We are interested in classifying our study period into periods of high versus low U.S. inflation as well as periods of high versus low growth in U.S. GDP.

To measure high and low inflation, we need to generate an historical long-term mean inflation rate as a proxy for trend-level inflation in the U.S. We do so by using five years of monthly US Bureau of Labor Statistics Urban CPI data preceding the beginning of our study period. For each month in that historical period, we compute monthly inflation as the percent change in CPI. We compute a chain-linked series of quarterly inflation rates from monthly inflation rates; we then calculate the mean of quarterly inflation rates as the mean of inflation rates from the 20 prior quarters preceding our study period. If the sign of the difference between any given quarterly inflation rate in the study period and mean quarterly inflation rate (i.e., *deviation*) is positive for a given quarter, that quarter is classified as a high inflation quarter;

conversely, if the sign of that difference (i.e., *deviation*) is negative for a given quarter, that quarter is classified as a low inflation quarter.

Similarly, to measure high and low growth in GDP, we estimate a measure of *normal* GDP growth to which quarterly values are compared. We collect data on U.S. GDP growth rates (i.e., percentage changes in quarterly real GDP numbers) for the five years preceding the beginning of our study period. We compute the mean U.S. GDP growth rate over the twenty preceding quarters (five years) then construct a *deviation* variable for GDP growth for each of our five quarterly study periods by subtracting mean GDP growth from each of the five quarterly GDP growth rates. If the sign of the difference (i.e., *deviation*) is positive for a given quarter in our study period, this quarter is classified as a "high" economic growth quarter, and conversely if the sign of the difference (i.e., deviation) is negative for a given quarter in our study period, that quarter is classified as a "low" economic growth quarter.

Table 6 presents results based on our first contextual factor of high versus low inflation. The estimation of Model (3) is presented in columns 1 and 4. Our results indicate that current quarter EPS changes, CAPX, GM and CASH are significant explanatory variables for predicting one-**quarter**-ahead EPS changes in periods of low inflation; however, only current quarter EPS changes, GM and CHG_MU are significant explanatory variables for predicting one-**quarter**-ahead EPS changes in periods of high inflation. Interestingly, use of fundamentals to predict one-**quarter**-ahead EPS changes become more effective during periods of high inflation versus low inflation as adjusted R^2 jumps from 43% to 78%. More specifically, we find that CAPX is statistically significant during periods of low inflation, but is statistically insignificant during periods of high inflation. This may be attributed to the possibility that periods of low inflation tend to coincide with periods of low interest rates which, in turn, translate into periods of lower

borrowing costs for the corporate sector and higher capital expenditures that are financed with borrowing at lower interest rates as a result of lower inflation in the economy. The lack of statistical significance of the CAPX variable during periods of high inflation may, however, be the result of managements' inclinations to: either not invest aggressively during those periods as a result of higher interest rates that embed higher inflation, or that they tend to finance lower levels of capital expenditure with equity funds more so than with debt during high inflation periods. Alternatively, there may be simply less variability in CAPX spending across our sample during periods of high inflation to allow us to obtain statistically significant results for that variable. We also find that CASH is statistically significant in low inflation periods but is not statistically significant in high inflation periods. This may be attributed to the possibility that periods of low inflation may also coincide with periods of sluggish lower aggregate demand, lower capacity utilization and higher uncertainty in the economy leading companies to desire to hold more cash during those periods.

Results in Table 6 (columns 2 and 3 for analysts and whisperers forecasts of EPS changes, respectively, during periods of low inflation, and columns 5and 6 for analysts and whisperers forecasts of EPS changes, respectively, during periods of high inflation) indicate that during periods of low inflation, although both analysts and whisperers use fundamental signals, whisperers appear to have a better understanding of associations between fundamental signals and one-**quarter**-ahead EPS changes than analysts as evidenced by the difference in the adjusted R^2 between the two models which increases from 24% to 31%. This may be due to the fact that whisperers use CASH, CHG_MU and GM in their predictions while analysts do not. Neither whisperers nor analysts, however, use any fundamentals to predict quarterly EPS changes in periods of high inflation.

Table 7 presents the analysis of the second contextual factor, GDP. Estimates of Model (3) are presented in columns 1 and 4. Our results indicate that current-quarter EPS changes, INV, AR, CAPX, GM and CHG_MU are significant explanatory variables for predicting quarterly EPS changes in periods of high GDP growth; however, only current-quarter EPS changes is significant for predicting quarterly EPS changes in periods of low GDP. Interestingly, the use of fundamentals to predict one-**quarter**-ahead EPS changes almost triples in periods of high GDP versus low GDP with adjusted R^2 of 75% and 26%, respectively.

We find that coefficients on five fundamental signals (INV, AR, CAPX, GM and CHG_MU) are statistically significant in periods of high real economic growth, but are statistically insignificant in periods of low real economic growth. This may be attributed to the fact that during periods of strong economic growth, there is less inventory buildup, more corporate sales growth, which translates to higher accounts receivable, and higher gross profit margins as a result of charging higher prices to customers who are more likely able to absorb price increases during a strong than a weak economy. In addition, it is during those periods of strong economic growth that companies are likely to embark on aggressive capital spending campaigns, and hence statistical significance of the CAPX variable. The reverse holds true during periods of slow economic growth which are characterized by periods of slower CAPX spending, slower sales growth, less AR outstanding, faster inventory buildup, and increased pressures to reduce prices to induce sales growth.

Table 7, columns 2 and 3 (5 and 6) present the results of analysts' and whisperers' forecasts of EPS changes, respectively, for periods of low (high) GDP growth. In periods of high GDP growth, although both analysts and whisperers use fundamental signals, whisperers appear to have a better understanding of associations between fundamental signals and one-

quarter-ahead EPS changes than analysts, as indicated by differences in the corresponding models' adjusted R^2 which jump from 8% to 16%. As shown, whisperers use current-quarter EPS changes and CAPX to forecast EPS changes, while analysts do not. Although neither whisperers nor analysts use any fundamentals to predict quarterly EPS changes in periods of low GDP growth, they both use current-quarter's EPS changes when making their forecasts of EPS changes.

Since we found statistically significant results for periods of low inflation and high GDP, we combined these two contextual factors to examine their effect on forecasts of EPS changes by both whisperers and analysts, and report these results in Table 8. As noted in column 1, current-quarter's EPS changes, CAPX, GM and CASH are statistically significant which are the same variables found to be significant in periods of low inflation (see Table 6). Since INV, AR and CHG_MU are not significant in the combined periods, it appears as though inflation is more important than GDP in estimating EPS changes. When comparing analysts (column 2) and whisperers (column 3), whisperers again appear to have a better understanding of the use of fundamental signals in predicting one-**quarter**-ahead EPS changes as indicated by a higher adjusted R^2, and the fact that whisperers use GM as an additional signal, but analysts do not.

In conclusion, with respect to inflation, we find that use of fundamentals to predict one-**quarter**-ahead EPS changes almost doubles in periods of high inflation relative to low inflation, with adjusted R^2 of 78% versus 43%, respectively; however, neither whisperers nor analysts use any fundamentals to predict quarterly EPS changes in periods of high inflation. In contrast, for periods of low inflation, although both analysts and whisperers use fundamental signals, whisperers have a better understanding of the association between fundamental signals and one-**quarter**-ahead EPS changes than analysts as indicated by differences in adjusted R^2 of 31% and

24%, respectively, and the fact that whisperers use CASH, CHG_MU and GM in their predictions while analysts do not. With respect to GDP, we find that coefficients of five fundamental signals (INV, AR, CAPX, GM and CHG_MU) are statistically significant, and that these variables appear to be useful for predicting one-**quarter**-ahead EPS changes in periods of high real economic activity, but are statistically insignificant in periods of low real economic activity as the adjusted R^2 almost triples from 26% to 75%. In periods of high GDP growth, although both analysts and whisperers use fundamental signals, whisperers appear to have a better understanding of the associations between fundamental signals and one-**quarter**-ahead EPS changes than do analysts as indicated by differences in adjusted R^2 of 16% and 8%, respectively, which may be due to the fact that whisperers use current-quarter EPS changes and CAPX in their predictions while analysts do not.

VII. SUMMARY AND CONCLUSIONS

We extend previous evidence found in the literature on the relevance of fundamental accounting signals for forecasting annual EPS changes using quarterly data. When we regress one-**quarter**-ahead EPS changes on current-quarter EPS changes only, we find that the two are negatively associated; evidence that is in line with earlier studies that used annual data. When we regress one-**quarter**-ahead EPS changes on six fundamental signals used by Lev & Thiagarajan [1993] in addition to current-quarter EPS changes, we find that three signals, Inventory (INV), Accounts receivable (AR), and Gross margin (GM) are statistically significant and incrementally add to the first model's explanatory power. Third, we augment the second model by including twelve additional fundamental signals introduced by Lambert [2011] and find that only one of the twelve additional variables, Change in Mark-up (CHG_MU), which is related to sales and cost of goods sold, or, alternatively, gross margin is statistically significant.

Next, we contrast analysts' and whisperers' use of fundamental accounting signals when forecasting one-**quarter**-ahead EPS changes. We find that whisperers use more information that is contained in fundamental signals than do analysts as confirmed by more statistically significant coefficients for the different signals, and a higher adjusted R^2 for whisperers' than for analysts' forecast model of EPS changes. We also analyze the efficiency with which analysts and whisperers use fundamental signals when making their one-**quarte**r-ahead forecasts of EPS changes by regressing forecasts errors from each group's model onto the different fundamental signals along with current-quarter EPS changes. We find that whisperers do better at embedding information from fundamental signals and current EPS changes when forecasting future EPS changes compared to analysts.

Lastly, we examine the impact of two contextual factors: domestic inflation rate and real GDP growth on analysts' and whisperers' forecasts of EPS changes. We characterize each of the five quarters in our study period as being either one of high or low inflation or one of high or low GDP growth, by comparing each quarter's inflation rate and GDP growth rate with their corresponding means calculated from the five years (or twenty quarters) preceding the beginning of our study period. We find that whisperers use fundamentals more effectively to predict one-**quarte**r-ahead EPS changes than do analysts particularly during periods of low inflation and high GDP growth as evidenced by their correspondingly higher adjusted R^2. However, neither group uses fundamentals effectively during periods of high inflation or low GDP growth. Variables related to sales, such as INV, AR, GM, in addition to CAPX, have statistically significant coefficients during periods of high GDP growth which may be attributed to the favorable economic climate during those periods. The reverse holds true during periods of low GDP growth. Since we find statistically significant results for periods of low inflation

and high GDP growth, we examine forecasts of one-**quarter**-ahead EPS changes by analysts and whisperers during those joint periods. The results confirm that whisperers are still better than analysts in using publicly available information contained in fundamental accounting signals to forecast one-**quarter**-ahead EPS changes during those periods.

The evidence presented in this study favors whisperers over analysts as more effective users of accounting information to make unconditional or conditional (on contextual factors) forecasts of one-**quarter**-ahead EPS changes. However, whisperers are not substitutes for analysts as each uses a different subset of fundamental accounting signals and each has unique information to provide to the market. Finally, the results shed light on how analysts and whisperers develop their forecasts of one-**quarter**-ahead EPS changes, how their use of fundamental accounting signals differ, and how the impact of inflation and GDP levels effect their use of the signals. This knowledge allows market participants to better use both forecast when making investment decisions.

Our findings are subject to limitations. First, we have a limited data set and time period resulting from the necessity of having to hand collect whisper forecasts during each earnings announcement period. Currently, historical whisper data are not available. Therefore, the findings may only be relevant to the sample firms and time period covered. Additionally, the model specifications may suffer from correlated omitted variables if there are other fundamental accounting signals that are used by either analysts or whisperers in forecasting one-**quarter**-ahead EPS.

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TABLE 1
Variable Definitions

The fundamental definitions are consistent with Lambert (2011, Table 2 pages 43-45 and Table 4 pages 50-52). The percent change is the quarterly change in the variable from the average of the prior 2 quarters.

$INV_{i,q}$ = percent change in inventory – percent change in sales for company *i* in quarter *q;*

$AR_{i,q}$ = percent change in accounts receivable – percent change in sales for company *i* in quarter *q;*

$CAPX_{i,q}$ = percent change in an industry's capital expenditures – percent change in capital expenditures for company *i* in quarter *q;*

$GM_{i,q}$ = percent change in sales – percent change in gross margin for company *i* in quarter *q;*

$S\&A_{i,q}$ = percent change in selling, general and administrative expenses – percent change in sales for company *i* in quarter *q;*

$ETR_{i,q}$ = (average tax rate for the prior three quarters – the tax rate for the current quarter) * the change in EPS for the current year for company *i* in quarter *q;*

$MKTSHR_{i,q}$ = sales/sales of all firms in the same 4-digit SIC code industry for company *i* in quarter *q;*

$CHG\_MKTSHR_{i,q}$ = percent change in MKTSHR for company *i* in quarter *q;*

$MU_{i,q}$ = sales – cost of goods sold/cost of goods sold for company *i* in quarter *q;*

$CHG\_MU_{i,q}$ = percentage change in MU for company *i* in quarter *q;*

$FCF_{i,q}$ = free cash flow define as operating cash flows – capital expenditures – dividends/total assets for company *i* in quarter *q;*

$CHG\_FCF_{i,q}$ = percentage change in FCF for company *i* in quarter *q;*

$CASH_{i,q}$ = cash/total assets for company *i* in quarter*;*

$CHG\_CASH_{i,q}$ = percent change in CASH for company *i* in quarter *q;*

$DEBT\_AT_{i,q}$ = total liabilities/total assets for company *i* in quarter *q;*

$CHG\_DEBT\_AT_{i,q}$ = percent change in DEBT_AT for company *i* in quarter *q;*

$DISC\_INC_{i,q}$ = discretionary income defined as sales – cost of goods sold – depreciation – taxes – dividends/sales for company *i* in quarter *q;*

$OP\_LEV_{i,q}$ = operating leverage defined as income before extraordinary items + selling and administrative expenses + depreciation/income before extraordinary items for company *i* in quarter *q;*

$AF_{i,q}$ = mean quarterly analysts' EPS forecasts on the last day prior to the earnings announcement date from the Institutional Brokers Estimates System database (IBES) for company *i* in quarter *q;*

$WF_{i,q}$ = mean quarterly whisperers' EPS forecasts manually collected from Whispernumber.com for company *i* in quarter *q;*

TABLE 2
Descriptive Statistics for the 219 Firm-quarter Observations

Variable Name	Mean	Standard Deviation	Minimum	Median	Maximum
$(EPS_{i,,q+1}-EPS_{i,q})/P_q$	-0.0003	0.0237	-0.2749	0.0010	0.1060
$(EPS_{i,q}-EPS_{i,q-1})/P_{q-1}$	0.0042	0.0361	-0.1831	0.0015	0.4205
$(AF_{i,,q+1}-EPS_{i,q})/P_q$	-0.0003	0.0110	-0.0689	0.0000	0.0734
$(WF_{i,,q+1}-EPS_{i,q})/P_q$	-0.0000	0.0103	-0.0559	-0.0002	0.0729
INV	-0.0108	0.2758	-1.1999	-0.0062	2.1000
AR	-0.0186	0.1876	-1.0602	-0.0080	1.0007
CAPX	0.0189	0.2973	-1.0797	0.0131	0.9647
GM	-0.0053	0.0934	-0.7320	0.0003	0.5227
S&A	-0.0331	0.1953	-1.2247	-0.0214	0.7012
ETR	-0.0176	0.2640	-3.7690	0.0000	0.8403
MKTSHR	0.3097	0.2743	0.0039	0.2255	0.9931
CHG_MKTSHR	0.0159	0.1266	-0.5125	0.0042	0.7551
MU	2.0386	3.6050	0.0344	0.9990	20.9645
CHG_MU	0.0019	0.1434	-0.5990	-0.0021	0.7346
FCF	0.0390	0.0553	-0.1034	0.0298	0.2939
CHG_FCF	-0.1648	4.0936	-24.8004	0.1223	25.5333
CASH	0.1705	0.1482	0.0013	0.1222	0.6441
CHG_CASH	0.0385	0.3536	-0.8251	0.0184	2.2922
DEBT_AT	0.5601	0.2057	0.2054	0.5723	1.0899
CHG_DEBT_AT	0.0016	0.0563	-0.1395	-0.0048	0.3459
DISC_INC	0.0680	0.1076	-0.2945	0.0504	0.4162
OP_LEV	14.2459	133.3474	-71.4872	3.2736	1,960.0000

See Table 1 for variable definitions.