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Essays on Management Earnings Forecasts

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INTRODUCTION

Management earnings forecasts represent an important form of corporate voluntary disclosure as they deal with future expectation about firms' performance. Research documents that forecasts have become a primary source of "value relevant" information and are valued by investors far more than other forms of disclosure (Rogers and Buskirk, 2009). Consequentially, there is significant demand from capital market participants for the disclosure of earnings forecasts by managers (Healy and Palepu, 2001).

The forecasting practice goes back to the 1970s when managers began privately to convey information about firm value and prospects to big investors. The practice then grew quickly until 2000, when Regulation Fair Disclosure was introduced and required all the information disclosed to be of public domain, thus avoiding the communication made in favor of particular categories of stakeholders. This contributes to change companies' disclosure practice. Public information is indeed subject to scrutiny and managers commit themselves when issuing the first forecast.

The accounting literature addresses several issues related to management forecasts, including the rationale behind the decision to voluntarily release them. Many of the motivations managers have for issuing earnings forecasts are in line with those of shareholders. That is, the supply of and the demand for guidance is assumed to be largely driven by stock price, with managers issuing forecasts to reduce the asymmetry in information between managers and analysts or investors (Ajinkya and Gift 1984; Verrecchia 2001). Lower information asymmetry is viewed as desirable because it is associated with higher liquidity (Diamond and Verrecchia, 1991) and lower cost of capital (Leuz and Verrecchia, 2000). However, the subsequent use and dissemination of information by analysts and stakeholders depends primarily on the form and the characteristics of disclosure itself (Beyer et al., 2010).

Despite the regulation requirements, managers have considerable discretion over the forecasting activity as they may decide not only the content of disclosure (i.e. earnings news) but even its "inner" characteristics. Nevertheless, the examination of forecast characteristics and their role as part of a wider disclosure strategy is still an open question. As Hirst et al. (2008) point out: *"…when managers issue management earnings forecasts, they also must consider the characteristics associated with those forecasts. That is, should they forecast just earnings or also other line items on the income statement? Should the forecasts also include explanations as to why the forecasts are plausible? We believe that great potential exists for theory refinement and/or development to address management's choice of forecast characteristics".*

Recently research has started examining the time-series patterns of earnings forecasts and explored the dynamic nature of the phenomenon. A survey by Graham et al. (2005) suggests that, when making guidance decisions, managers place increasing weight on being consistent with their past guidance, hence they work to maintain predictability in earnings and financial disclosure.

To date, however, the accounting research misses a fundamental piece of the puzzle: analyzing earnings forecasts characteristics in a multi-period setting. Costs and benefits exist for including one characteristic or another, and pursue it. Therefore, it is unclear how managers choose between different characteristics across time, assuming that they continuously issue earnings forecasts, and which are the effects of these choices. Bridging together these recent studies, this dissertation explores the multi-period nature of management earnings forecasts characteristics.

The dissertation is in three research papers. The first two are linked to each other, being the second the logic prosecution of the first.

The first chapter, "*An examination of the determinants of Management Earnings Forecasts Consistency*", examines the role of the main determinants identified in the literature in explaining guidance patterns in terms of characteristics. The second chapter, "*Consequences of Management Earnings Forecasts Consistency*", studies the effect of earnings forecasts consistency on the properties of financial analysts' estimates. The third chapter, "*Management Earnings Forecasts, Impression Management and the Probability of Missing the Earnings Target*", explores whether the qualitative features of management earnings forecasts have predictive power in explaining the probability of firms missing the earnings expectations.

More in detail, the first chapter investigates the iterative nature of earnings forecasts with specific reference to the characteristics, and provide empirical evidence on the cross-sectional determinants of consistency. In particular, research analyzing the nature of earnings forecasts characteristics in a multi-period perspective and what potentially determines their stickiness across time is still scant (Graham et al. 2005; Einhorn and Ziv, 2008). This paper aims at gaining a better understanding of the choices managers make after they decide to issue an earnings forecast. Preliminary results suggest that CEO experience, industry competition as well as firm's size contribute to explain the stickiness of forecasts characteristics measured from a level-based perspective. Apparently more experienced managers reserve attention to additional details of guidance and are more inclined to maintain forecasts characteristics unchanged either to aid stakeholders, providing them with a familiar base of attributes to interpret the earnings estimates, or signal their managerial style. On the other side, bigger firms in less concentrated, thus more competitive, industry are more likely to develop consistent characteristics policies.

The paper makes a contribution to the disclosure theory in the setting of earnings forecast, providing evidence that the choices related to forecasts characteristics are path-dependent and go far beyond the mere decision of nourishing or stopping guidance activity. Also, the paper adds to the current debate on guidance practice. It suggests that over and beyond the measure of guidance frequency, the study of the inner characteristics of earnings forecasts in a multi-period perspective especially deserves attention given that managers have greater discretion over their choice and external parties (e.g. analysts' behavior) may be influenced by them.

The second chapter exploits a longitudinal perspective to study the influence of earnings forecasts consistency on the information environment. While recent research examines the negative consequences associated with interrupting a disclosure precedent (Houston et al., 2010; Chen et al., 2011), empirical evidence on the consequences of keeping certain characteristics unchanged is still absent. This paper examines whether managers issue consistent earnings forecasts in terms of characteristics, whether financial analysts recognize consistent guidance patterns and how they react. In other words, it investigates from a longitudinal perspective earnings forecasts' characteristics and the relative effect on analysts activity, while previous literature on dynamic disclosure only assess the extent to which firms' strategic disclosure behavior in the past affects their prosperity to provide voluntary disclosures in the future.

Preliminary results suggest that a strong level of consistency (e.g. the whole set of characteristics remains unchanged over time) positively affects a firm's information environment, helping analysts to align their expectations with managers. When looking at consistent characteristics individually, the positive effect on analyst dispersion seems to be driven by all the three characteristics (e.g. precision, disaggregation and additional information) but with a larger impact of consistency in precision. Accuracy is positively influenced by consistency in the level of disaggregation, while analyst coverage increases are attributable to the level of precision being unchanged from year to year.

This chapter adds to the literature in two ways. It extends the disclosure research by providing evidence that consistency in forecasts characteristics contribute to keep the level of information asymmetry unchanged over time (given the different level of detail each attribute provides), thus benefiting analysts' response to disclosure over time. Further, it contributes to the recent stream of literature examining firms that stop providing earnings guidance (Houston et al. 2010; Chen et al. 2011) and demonstrates that changes in guidance patterns may not necessarily relate to the interruption of guidance itself, but could be analyzed at a finer level by peeking into each document and examining its inner content.

The third chapter investigates whether the qualitative features of management earnings forecasts have predictive power in explaining firms' missing the earnings target. More precisely, it tests whether the consistency in guidance characteristics and the tone accompanying the earnings projections can significantly predict the probability that a firm misses the earnings expectations in the subsequent period. The results suggest that consistency in precision and disaggregation positively influence the probability of missing the target in the subsequent fiscal year, while the impression management score is negatively related to it. When examining the different specifications of consistency, I find that earnings projections consistently given in the form of qualitative description, disaggregated at the expenses level and accompanied by attributions are positively associated with the probability of missing the earnings target in the subsequent period.

This paper represents an incremental contribution to the collective understanding of the phenomenon of firms' missing the earnings target, while adding to the research on guidance characteristics and their role as part of a wider disclosure strategy. Also, the paper extends the impression management literature by providing evidence of a link between managers' use of tone in press releases and future earnings expectations.

The evidence provided by the three research papers should be of interest to accounting researchers who study corporate disclosure as well as to executives who are responsible of making corporate disclosure decisions. [1]

[1] The three research papers are preliminary versions. Further comments received are going to be included in view of future submission to accounting journals.

CHAPTER 1

An examination of the determinants of Management Earnings Forecasts Consistency

November 2014

Preliminary Version: Do not Cite / Circulate

This paper has been presented at Emory University. I am grateful to my advisor, Saverio Bozzolan, and Grace Pownall for their guidance. Some comments still need to be incorporated. All errors or omissions are mine.

An examination of the determinants of Management Earnings Forecasts Consistency

ABSTRACT

This paper examines whether firms engage in consistent pattern of management earnings forecast characteristics and which determinants most likely explain the phenomenon. Building on previous literature on guidance characteristics, I develop a measure of consistency considering three attributes: precision, level of disaggregation and additional qualitative information. I classify firm as "consistent" based on persistence of characteristics over time. The paper investigates management earnings forecasts from a cross-sectional perspective and attempts to shed new light on the iterative nature of management earnings forecasts characteristics, which appear to be the least well-understood component of the forecasting activity. Preliminary results suggest that CEO experience, industry competition as well as firm's size contribute to explain the stickiness of forecasts characteristics measured from a level-based perspective. Among the factors responsible of earnings forecasts consistency at the individual characteristic level, firm's size is a common determinant for all characteristics specifications. Consistency in precision is driven by performance. Consistency in disaggregation is determined by litigations risk, uncertainty and analyst coverage, while consistency in additional information depends on the experience accumulated by the CEO and the level of uncertainty in firms' environment.

Keywords: Management Earnings Forecasts, Consistency, Characteristics, Determinants

Data Availability: Data used in this study are available from public sources indicated in the text.

1.1 INTRODUCTION

Management earnings forecasts represent an important form of corporate voluntary disclosures as they deal with future expectations about firms' performance. Research documents that forecasts have become a primary source of "value relevant" information and are valued by investors far more than other forms of disclosure (Rogers and Buskirk, 2009). In order to assess firm's value, external parties, such as analysts, are engaged in the understanding of company's internal strategies and future performance to generate earnings forecasts. Consequentially, there is significant demand from capital market participants for the disclosure of earnings forecasts by managers (Healy and Palepu, 2001).

The rationale behind managers' decision to issue forecasts is based on their perceptions of the costs and benefits to the firm (i.e. higher liquidity and lower capital costs are weighted against proprietary and litigation costs) and to themselves (i.e effects on reputation and compensation).

Existing research primarily focuses on why managers choose to issue a forecast and the likely consequences of those decisions (e.g., Ajinkya and Gift 1984; Skinner 1994; Stocken 2000; Verrecchia 2001). In other words, it mainly address "antecedents" and "consequences".

Despite the regulation requirements, managers have considerable discretion over the forecasting activity (Baginski et al., 2004). They not only decide the timing and the informative content of disclosure but also its characteristics[2]. As Hirst et al. (2008) point out:

"…when managers with high incentives issue management earnings forecasts, they also must consider the characteristics associated with those forecasts. That is, should they forecast just earnings or also other line items on the income statement? Should the forecasts also include explanations as to why the forecasts are plausible? We believe that great potential exists for theory refinement and/or development to address management's choice of forecast characteristics".

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[2] As in Hirst et al. (2008), forecast characteristics are to be intended as properties or attributes of the earnings forecast *per se*.

In this respect, some studies examine single characteristics of earnings forecasts and how managers choose them. However, there is still relatively less research regarding the examination of forecast characteristics and their role as part of a continuous disclosure strategy. Research thus misses a fundamental piece of the puzzle that is analyzing the nature of the choice of earnings forecasts characteristics in a multi-period perspective and what potentially determine their stickiness from one period to the next (Graham et al. 2005, Lansford et al. 2013). This paper aims at gaining a better understanding of the additional choices managers make after they decide to issue an earnings forecast.

A recent stream of research on management earnings forecasts explores the dynamic dimension of the practice and focuses on the concept of consistency (Tang, 2012; Hilary et al. 2014). Consistency generally refers to persistence of a behavior over time and assumes that a correlation between a present action and the past exists, thus supporting a path dependency approach. The purpose of this study is to shed new light on the iterative nature of earnings forecasts with specific reference to their characteristics, and to provide empirical evidence on the cross-sectional determinants of consistency. In other words, the question arises as to which factors motivate firms' consistency over time in terms of forecast characteristics.

As first step, the paper tests some variables proposed by the accounting literature as determinants of forecasts characteristics (in a single period setting) in order to see whether they play a role also in a multi-period setting and justify consistency. These variables are: CEO experience, litigation risk, probability of revealing a bad news, level of competition, cumulative abnormal returns, uncertainty, forecast error and earnings surprise.

Using a sample of hand-collected management earnings forecasts press releases for the period 2005-2013, I develop a measure of consistency considering three characteristics: precision, level of disaggregation and additional qualitative information. I classify firm as "consistent" based on persistence of characteristics over time. Consistency may refer to the number of characteristics that are maintained unchanged from one period to the next, as well as to characteristics taken individually. The first measure is designed to capture the incremental level of consistency, while the second conveys insights into the specific role of a single attribute. I use both definitions and exploit a cross-sectional setting to test weather each of these dimensions is related to firm's and industry's specific characteristics. I test my predictions using both ordered and multinomial logistic models and the consistency constructs as dependent variables. Preliminary results suggest that among the identified variables, the experience of the CEO, the industry concentration as well as the firm's size more likely contribute to explain the stickiness of forecasts characteristics measured from a level-based perspective. On the other side, bigger firms in less concentrated, thus more competitive, industry are more likely to develop consistent characteristics policies.

Further, the results suggest that among the factors responsible of earnings forecasts consistency at the individual characteristic level, firm's size is a common determinant for all the three characteristics specifications. Consistency in precision is mainly driven by the earnings surprise, which is assumed to be related to performance. Consistency in disaggregation is influenced by litigations risk, the level of uncertainty and the number of analysts following a company, while consistency in the type of additional information depends on the experience accumulated by the CEO and the level of uncertainty.

Overall the literature suggest different rationale behind the managerial decision of issuing earnings forecasts, as well as to change or keep them, within a static framework. Prior studies, however, lack a multi-period approach to the study of earnings forecasts and the very few adopting a dynamic approach (Einhorn and Ziv, 2008; Tang, 2012; Hilary et al. 2014) do not consider the structure and attributes of the forecasts and their determinants, potentially missing an important piece of information.

Bridging together these recent studies, it is an interesting research question to examine earnings forecasts' structure from one fiscal year to the next and to study the related determinants.

To the best of my knowledge this is the first study developing a measure of consistency based on earnings forecasts characteristics and examining the related determinants. The paper makes a contribution to the disclosure theory, more precisely to the literature on earnings forecast, supporting that the choices related to forecasts characteristics are path dependent with respect to the past and goes far beyond the mere decision of nourishing or stopping guidance activity.

The rest of the paper is organized as follows. Section 2 discussed the relevant research and outlines plausible predictions. Section 3 describes the data and the research design. Section 4 reports the results from the empirical tests. Section 5 reports additional analysis. Section 6 concludes and discusses possible implications of the research.

1.2 THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

Hirst et al. (2008) categorize earnings forecasts as having three components: antecedents, characteristics, and consequences. Antecedents and consequences are the most investigated components, while forecast characteristics appear to be by far the least understood component, in terms of both theory and empirical research.

Many of the motivations managers have for issuing earnings forecasts are in line with those of shareholders and directed to reduce information asymmetry (Ajinkya and Gift 1984; Verrecchia 2001), which is associated with higher liquidity (Diamond and Verrecchia, 1991) and lower cost of capital (Leuz and Verrecchia, 2000). Managers are especially concerned about analysts' perceptions of guidance because failure to meet their expectations results in negative price revisions (Bartov et al., 2002) and adverse publicity for the firm (Skinner and Sloan, 2002). Previous research documents that managers may act to alter market earnings expectations (Matsumoto et al. 2002) or strategically manipulate the decisions of stakeholders (Bowen et al., 2005). Earnings guidance may also signal managerial ability and the fact that new information has been received by managers (Trueman, 1986), or management's desire to establish personal credibility and the need to build a strong investor base (Gibbins et al. 1990; Hutton and Stocken 2009). In their survey, Graham et al. (2005) confirm that managers issue voluntary disclosures, including earnings forecasts, to develop and maintain a reputation for accurate and transparent reporting. As a consequence, guiders are likely to spend greater time and resources on the guidance effort which in turn affect its characteristics.

Despite the regulation requirements, managers not only decide the timing and the informational content of disclosure but also its characteristics. Sedor (2002) notes that managers choose the characteristics of their communication to include "*concrete details and causal orderings that link current status, planned actions, and anticipated future outcomes*". Accounting research has acknowledged that structure is important to the understanding of financial disclosure. Bowen et al. (2005), for example, find that investors are more responsive to earnings metrics that managers emphasize.

Forecast characteristics pertain to the choices that a manager makes regarding the content of the forecast itself, such as: precision, level of disaggregation, and qualitative attributions (Hirst et al. 2008). To the extent that forecast characteristics are examined in the literature, they are primarily treated as exogenous variables (Baginski et al. 2004). Given that managers have greater control over forecast characteristics, it is striking that the decisions managers make about such characteristics are comparatively less well-understood (Choi et al. 2006). For example, we know relatively little about why managers decide to issue forecasts with external versus internal attributions and why they issue them in conjunction with other disclosures (Baginski et al. 2004, 17). Further, the alternative characteristics of forecasts are important as not all choices that managers make are equally relevant to investors. In sum, having chosen to issue an earnings forecast, the manager then faces a broad set of choices related to the attributes of that forecast.

I select three main characteristics from the leading literature on management earnings forecasts:

- precision,
- level of disaggregation,
- type of additional qualitative information.

With respect to precision, managers may issue earnings forecasts in four forms: (1) point estimates; (2) range estimates with a lower bound and an upper bound; (3) minimum estimates, which are often good news, or maximum estimates, which are often bad news; and (4) qualitative guidance. Qualitative forecasts are non-numerical forecasts, as for example: "*The company expects EPS to improve for the next fiscaly year*".

The form of the earnings estimate is crucial since it captures the precision of managers' beliefs about the future (King et al., 1990). More precise forecasts are generally perceived to reflect greater managerial certainty relative to less-precise forecasts (Hughes and Pae 2004). Baginski and Hassell (1997) examine the factors associated with managers' decisions to provide range forecasts versus point forecasts (which are more precise) and minimum/maximum forecasts (which are less precise). Using the forecast horizon, they document that imprecise forecasts are issued in presence of greater earnings uncertainty. Waymire (1985) finds that firms showing less uncertainty issue forecasts more often than more-volatile firms, which may lead to presume they will be able to provide subsequent consistent forecasts. Du et al. (2011) find that the use of range as opposed to point forecasts generally increases with firms' operating uncertainty and that range widens when operating uncertainty grows. Management forecast precision affects investors' confidence in the earnings estimate (Hirst et al. 1999; Libby et al. 2006) and more precise forecasts lead to greater analyst forecast revisions (Baginski et al. 2011). Whether forecast precision affects investors' price responses is although inconclusive (Pownall et al. 1993).

Research also finds that earnings forecasts made in the presence of analysts tend to be more precise compared to press releases, possibly because of the directness of the potential scrutiny from analysts (Bamber and Cheon 1998). Factors that are negatively associated with forecast precision include firm size and return volatility (Baginski and Hassell 1997). Negative news is also associated with less precise forecasts than is positive news (Choi et al., 2010).

Earnings forecasts may then vary in terms of levels of disaggregation. That is, managers can issue a forecast of only the bottom-line earnings number. Alternatively, they can issue earnings forecasts along with forecasts of other key line items of the income statement (i.e. revenues, cost of goods sold, SGA expenses, etc.). Disaggregated forecasts of income statement line items are well-defined accounting data in contrast to other supplementary disclosures.

Han and Wild (1991) report that 40% of management earnings guidance is accompanied by revenue guidance and find that managers do so when the former is insufficient to reduce the earnings expectation gap between managers and analysts. Tucker (2007) document that the likelihood of disclosing other components along with the guidance is associated with good news and high analysts following. Lansford et al. (2013) find that nearly one in three S&P 500 companies that provide annual earnings forecasts also provides disaggregated forecasts consisting of earnings, revenue and specific expenses. They report that the probability of full disaggregation increases with institutional ownership and intangible assets, and decreases with the value-relevance of earnings. Also, analysts respond more quickly to fully disaggregated forecasts and disaggregation is associated with larger absolute analyst forecast revisions. Merkley et al. (2013) suggest that disaggregation increases the credibility of both good news and bad news forecasts when earnings are otherwise more difficult to predict. That is, disaggregation is especially helpful to analysts when they face a particularly difficult forecasting task because management forecasts of bottom-line EPS are likely to be noisy. Finally, the disaggregation of the earnings component may incur significant proprietary disclosure costs, helping competitors and discouraging managers from disclosing (Verrecchia, 1983). Assuming that proprietary disclosure costs are proportional to industry competition, we can expect that consistency in disaggregation decreases with industry competition.

Managers then supplement earnings guidance with additional information in the form of comments, updates or attributions. Officers' comments are informative beyond the announcement of the earnings (Francis et al. 2002). A substantial number of managers voluntarily choose to link forecasted performance with internal causes (i.e., their actions), external causes (i.e., the actions of parties external to the firm such as competitors, governmental regulators, and policy makers), or both. These are potentially important information to investors who engage in strategic analysis of financial statement information. Indeed, if the attributions are credible, they can enhance investors and analysts' understanding of the earnings estimates by providing additional information on the connection between factors and profitability (Baginski et al. 2004). Acknowledging that the information accompanying forecasts may be relevant per se' and contribute to highlight or conceal the value of the forecast is the assumption that differentiate this paper from research evaluating the numerical value of the forecast but ignoring all the other information accompanying the earnings projection. With respect to the latter, Baginski et al. (2004) find that nearly three out of four forecasts in their sample are accompanied by attributions explaining their forecasts. Also bad-news forecasts, maximum forecasts, and shorter-horizon forecasts are more likely to be accompanied by these attributions.

Gaining a better understanding of the choices that managers make once they decide to issue an earnings forecast is an important direction for both theory development and empirical research (Hirst et al. 2008). In this respect, however, research is still scarce.

A recent stream of research on management earnings forecasts explores the multi-period dimension of the practice and focuses on the concept of consistency. Tang (2012) argues that while guidance frequency is an intuitive indicator for "regular" guidance, it does not capture the pattern during which guidance has been issued. Using a measure of consistency based on presence/absence of a guidance in a given quarter/year, his study shows that firms are less likely to change their guidance practice following a consistent history. Hilary et al. (2014) develop another measure of consistency referring to earnings forecasts errors and find that managers who make consistent forecast errors have a greater ability to move prices and analyst forecast revisions, even after controlling for the effect of accuracy.

As first step, this paper tests the link between some of the variables already considered by the accounting literature as determinants of forecasts characteristics (in a single period), in order to see whether they also contribute to justify consistency.

Managers with less forecasting experience are shown to provide less accurate forecasts (Chen 2004). The lack of experience can manifest itself in different ways: less experienced managers can be less prompt at anticipating potential unexpected events with a negative impact on earnings, or less experienced at the game of guiding down analysts and investor expectations.

Management earnings forecasts are voluntary disclosures that typically reach a broad audience and significantly impact share value. Among other things, prior research suggests that fear of shareholder litigation, reputation concerns for accuracy, and concerns about adverse price movements provide strong incentives for managers to issue attainable forecasts. Given the voluntary nature of these forecasts and the compelling incentives for accuracy, plus the managerial incentives to meet earnings benchmarks through implicit guidance (Matsumoto 2002), it is puzzling whether managers would mislead stakeholders with changing forecast characteristic or not. Thus, I conjecture that more experienced managers will pay attention at additional details of guidance and will be inclined to maintain forecasts characteristics either to aid stakeholders providing them with a familiar base of attributes to interpret the earnings estimates, or to signal their managerial style (Bamber et al. 2010).

Prior research finds that managers supplement good-news earnings guidance with additional information to increase the credibility of the guidance. Skinner (1994) documents additional disclosure for bad news firms over short horizons. Hutton et al. (2003) consider the impact of supplementary statements on the informativeness of management earnings forecasts and find that managers issue qualitative disclosures with equal frequency for both good news and bad news forecasts, but that they issue more verifiable forward-looking statements for good news. Baginski et al. (2004) find that attributions are provided more often with bad news forecasts. Thus, I expect the effect of bad news on the multi-period choice of characteristics to be either positive or negative, and more likely depending on whether firms are already communicating expectations with a higher level of detail or not.

Each forecasts characteristic brings a different level of detail. When a pattern of consistent characteristics is violated because of a change in one or more of them we are in presence of a potential "break" that can affect (positively or negatively) the level of information asymmetry. For example, it could be the case of moving from a condition *x* of "given level of detail" to a condition *y* of "increasing level of detail" (i.e. from a range to a point forecast). Earnings forecast characteristics may thus incur significant proprietary disclosure costs as such disclosures may help firm's competitors (Verrecchia, 1983). Because proprietary disclosure costs increase with the intensity of industry competition, I expect the disclosure of forecasts characteristics to be sticky especially when industry competition is high.

Price reaction is usually measured over the three-day window centered on the earnings announcement date using standard market model procedures. Earnings forecasts characteristics can be consistent from one year to the next in an attempt to avoid legal liability (Baginski et al. 1997). Alternatively, managers might be playing with forecasts characteristics in an attempt to dampen price reaction.

Earnings are more difficult to predict when operations are more complex and highly sensitive to external factors, such as input prices. Under these circumstances, investors and analysts are more likely to demand earnings guidance to assist their analyses. The underlying uncertainty of operations may affect managers' confidence in their predictions, thus limiting the level of detail to convey and push them towards a stable, consistent, disclosure. To avoid missing their estimates or inflate market expectations, managers may be less likely to change guidance characteristics (Waymire, 1985; Verrecchia, 1990).

Based on the above considerations, I expect that some of the factors related to the choice of single-period characteristic are also related to consistency.

I first test consistency as a level-based measure and formalize the following hypothesis:

H1: The level-based measure of consistency, signaling the number of consistent characteristics, is associated with some determinants of single-period forecast characteristics.

I then apply the test to individual measures of consistency and formalize the following hypothesis:

H2: The characteristic-based measure of consistency, signaling consistency for each individual attribute, is associated with some determinants of single-period forecast characteristics.

1.3 DATA AND RESEARCH DESIGN

Sources

Data on management earnings forecasts are obtained from *Factiva* using the "*Press Release Newswire*" and "*Dow-Jones Business* News" sources for the North-America region. Financial analyst forecasts data are obtained from the Institutional Brokers Estimate System (*IBES)*. I use *Compustat* to collect financial data and *CRSP* to collect prices.

Sample Selection

I hand collect management earnings forecasts from press releases issued for the years 2005-2013. I use Factiva to download candidate management earnings forecasts and follow Baginski et al. (2004) to perform the search. Using business newswires Dow Jones Business News ("DJBN") and Press Release Newswire ("PRN"), I look for the following set of keywords: *"expects earnings", "expects net", "expects income", "expects losses", "expects profits", and "expects* *results".* In addition, I look for three parallel lists where "*expects"* is replaced alternatively by *"forecasts", "predicts", and "sees".* This search yields 9,304 candidate earnings forecasts observations (7,752 for DJBN and 1,552 for PRN) downloaded in batches of 100 announcements per .txt file and corresponding to 2,505 firms' observations. I treat the press release earnings forecast as unit of observation.

Each company identifier (referred to as "CO" in Factiva) is extracted from the downloaded text and, through a textual algorithm, matched to the more common Compustat company name and ticker identifier. I manually verify these automated "candidate matches". Following Gong et al. (2011), I exclude guidance issued in prior years if already existing for the current year because these long-term forecasts contain more earnings uncertainty, and are not comparable to forecasts issued during the current period. This process yielded a total of 5,434 forecast observations, corresponding to 1,603 firm observations which include both quarterly and annual guidance. Press releases are content analyzed and forecast characteristics related information is manually reported in the classification scheme as in figure 1.

After a first screening of the reported headlines, 535 press releases are deleted as they do not refer to companies' future earnings but to "footnotes", "recap", "correction", "market talk" or appear to be generic. The sample is then split into annual and quarterly forecasts, based on the forecasting period. For the purpose of this study only the annual subsample is considered[3], which yields a total of 2,263 observations corresponding to 946 firms. I require sample firms to exist in Compustat and CRSP database, leading to a final sample of 1,843 forecast observations.

Measures of Consistency

[3] I plan to use the quarterly sample of forecasts for the purpose of additional analysis.

Consistent with Tang (2012), the hypotheses are tested on annual earnings forecasts although this can limit my sample size. I use two alternative measures of management earnings forecasts consistency. The first proxy is a level-based measure and aims to capture the incremental level of consistency, thus providing insights into how many characteristics remain unchanged from one period to the next. While this is more an intuitive indicator of whether managers are willing to keep the whole set of attributes unchanged over time, it does not fully capture individual characteristics' behavior, thus losing sight of each one's nature. To overcome this concern, I develop a second measure of consistency based on the pattern of individual characteristics, as to draw inferences on each one separately.

More precisely, three key guidance characteristics are taken from previous literature[4] and defined as:

- Forecast precision: which articulates in "point", "range", "open-ended" and "qualitative", based on the form that the guidance takes;
- Level of disaggregation: which articulates in "earnings news only", "earnings plus revenue or sale items", "earnings plus at least one major expense" and "earnings plus detailed income statements/balance sheet items", based on the number of line items for which a projection is reported;
- Additional qualitative information: which articulates in "earnings explanation" (either internal or external attributions), "CEO/CFO comment" and "update", based on the type of additional disclosure that managers choose to provide.

For both measures, I define earnings guidance to be "consistent" based on the persistence of characteristics (a set, or a single one) from one fiscal year (*t-1*) to the next (*t*). This requires an earnings forecast to exist for at least two consecutive years. I assign a score at each earnings

[4] For an extended review of the topic see Hirst et al. (2008).

forecast based on the characteristics to which consistency applies, binding the definition to preceding fiscal year independently from a sequence of quarters. I conjecture that firms providing annual guidance with a certain set of characteristics at year *t-1* will be prone to provide guidance reflecting previous characteristics composition at year *t* under some circumstances.

[INSERT TABLE 1 HERE]

The first measure of consistency refers to three alternative levels of consistency defined as follows (setting 1):

- *Strong consistency*: if all the three characteristics in question - precision, disaggregation and additional information - in year *t* are identical to year *t-1*.
- *Semi-strong con*sistency: if two[5] out of three characteristics in year *t* are identical to year *t-1*.
- *Weak consistency*: if one out of three[6] characteristics of interest in year *t* is identical to year *t-1*.

The second measure of consistency represents a more specific measure and allows to draw inferences on the role and importance of each forecasts' attributes. In order to capture consistency at the individual characteristic-level (setting 2), I define the following categories[7]:

- *Consistency in precision*: if the level of precision (i.e. point, range, open ended or qualitative) in year *t* is identical to year *t-1*;
- *Consistency in disaggregation*: if the level of disaggregation (earnings only, revenues or sale, at least one major expense or detailed line items) in year *t* is identical to year *t-1*;
- *Consistency in additional qualitative information*: if the type of additional qualitative information (earnings explanation, CEO/CFO comment, update) in year *t* is identical to year *t-1*, 0 otherwise.

[5] Note that I strictly bind the definition of semi-strong consistency to the similarity of "two" dimensions instead of "at least two" in order to preserve mutually exclusive categories of consistency.
[6] Note that, as for semi-strong consistency, I strictly bind the definition of weak consistency to the similarity of "one" dimension instead of "at least one" in order to preserve mutually exclusive categories of consistency.
[7] See Table 1 for some examples of consistency.

Empirical Design

To test the set of hypotheses, I use the measures of consistency as dependent variables and examine whether firm-specific and industry-specific factors likely explain the probability to report a consistent pattern of earnings forecasts characteristics.

I first run an ordered logistic regression using *CONS_LEV*, the level-based proxy for consistency, as the dependent variable. Note that *CONS_LEV* is an ordinal variable that takes the value of "0" if the forecast displays no consistency, "1" if the forecast reports a *weak* consistency, "2" if the forecast reports a *semi-strong* consistency and "3" if the forecast reports a *strong* consistency.

Several control variables are added to the test model. The return on assets (*ROA*) is employed to control for differences in firm's performance. The logarithm of the firm's total sales (*L_SALE*) and leverage (*LEV*) are included, in order to control for firm's size and specific aspects of the firm's information environment as well as the level of external scrutiny. To control for various aspects related to firm-specific environment, I include the number of analysts following the firms (*FOLLOW*) and the dispersion in analysts' forecasts (*DISP*) relative to the earnings of year t. Finally, the average error of the forecasts relative to year t (*ERR*) captures the firm's forecasting ability. A more detailed description of all variables is provided in the appendix.[8]

The explanatory variables are:

- CEO experience, defined as the total years of experience accumulated by the CEO;
- Competition, defined through the Herfindal index which the sum of squared product market shares of firms in the industry (48 Fama–French industry classification);

[8] All the continuous variables are winsorized at the first and 99th percentile. All the coefficients resulting from the estimations are tested using the Wald test, which lead to reject the null hypothesis that they are simultaneously equal to zero. Different measures of fit have been calculated in order to test whether each of the model used is adequate, although this cannot ensure that selecting a model that maximize the value of a given measure results in a model that is optimal in any sense.

- Litigation, defined as a dummy variable for whether the firm is in a high-litigation industry;
- Cumulative abnormal returns, defined as the absolute value of firm's three day size-adjusted return centered on the issuance date of the earnings announcement;
- Uncertainty, defined as the logarithm of the calendar days between the earnings forecast issuance date and the earnings announcement date;
- Bad news, is an indicator variable equal to 1 if the company's earnings are lower than the most recent analyst consensus from the IBES summary data before the disclosure event, 0 otherwise;
- Forecast error, defined as the average error of the forecasts issued by the firm relative to the earnings that is being currently announced;
- Analysts coverage, defined as the average number of analysts following a comany;
- Dispersion, defined as standard deviation of analysts' EPS forecasts for year t in the most recent consensus;
- Meeting-Beating behavior, defined as an indicator variable equal to 1 if realized annual EPS is greater than or equal to analysts' consensus forecasts in year t.

The models are as follows:

Model 1

$$
\begin{aligned}
CONS\_LEV_{it} = {} & \beta_0 + \beta_1\, CEO\_EXP_{it} + \beta_2\, HH_{it} + \beta_3\, LIT_{it} + \beta_4\, EARN\_DIFF_{it} + \beta_5\, CAR_{it} + \\
& + \beta_6\, L\_DAYS_{it} + \beta_7\, BAD\_NEWS_{it} + \beta_8\, ERR_{it} + \beta_9\, FOLLOW_{it} + \beta_{10}\, DISP_{it} + \\
& + \beta_{11}\, MEET_{it} + \beta_{12}\, ROA_{it} + \beta_{13}\, L\_SALE_{it} + \beta_{14}\, LEV_{it} + \varepsilon. \qquad (1)
\end{aligned}
$$

Model 2

$$
\begin{aligned}
CONS\_LEV_{it} = {} & \beta_0 + \beta_1\, CEO\_EXP_{it} + \beta_2\, HH_{it} + \beta_3\, LIT_{it} + \beta_4\, EARN\_DIFF_{it} + \beta_5\, CAR_{it} + \\
& + \beta_6\, L\_DAYS_{it} + \beta_7\, BAD\_NEWS_{it} + \beta_8\, ERR_{it} + \beta_9\, FOLLOW_{it} + \beta_{10}\, DISP_{it} + \\
& + \beta_{11}\, MEET_{it} + \beta_{12}\, ROA_{it} + \beta_{13}\, L\_SALE_{it} + \beta_{14}\, LEV_{it} + \beta_{15}\, LAG\_CONS\_LEV_{it} + \varepsilon. \qquad (1a)
\end{aligned}
$$

I then run a multinomial logistic regression using *CONS_CHAR*, the characteristic-based proxy for consistency, as the dependent variable. Note that *CONS_ CHAR* is a categorical variable that takes the value of "0" if the forecast displays no consistency, which is used as comparison group, "1" if the forecast is consistent in *precision*, "2" if the forecast is consistent in disaggregation and "3" if the forecast is consistent in the additional qualitative information. The above mentioned tests are repeated and the set of control variables included. The models are as follows:

Model 3

$$CONS\_CHAR_{it} = \beta_0 + \beta_1\, CEO\_EXP_{it} + \beta_2\, HH_{it} + \beta_3\, LIT_{it} + \beta_4\, EARN\_DIFF_{it} + \beta_5\, CAR_{it} + \beta_6\, L\_DAYS_{it} + \beta_7\, BAD\_NEWS_{it} + \beta_8\, ERR_{it} + \beta_9\, FOLLOW_{it} + \beta_{10}\, DISP_{it} + \beta_{11}\, MEET_{it} + \beta_{12}\, ROA_{it} + \beta_{13}\, L\_SALE_{it} + \beta_{14}\, LEV_{it} + \varepsilon. \tag{2}$$

Model 4

$$CONS\_CHAR_{it} = \beta_0 + \beta_1\, CEO\_EXP_{it} + \beta_2\, HH_{it} + \beta_3\, LIT_{it} + \beta_4\, EARN\_DIFF_{it} + \beta_5\, CAR_{it} + \beta_6\, L\_DAYS_{it} + \beta_7\, BAD\_NEWS_{it} + \beta_8\, ERR_{it} + \beta_9\, FOLLOW_{it} + \beta_{10}\, DISP_{it} + \beta_{11}\, MEET_{it} + \beta_{12}\, ROA_{it} + \beta_{13}\, L\_SALE_{it} + \beta_{14}\, LEV_{it} + \beta_{15}\, LAG\_CONS\_CHAR_{it} + \varepsilon. \tag{2a}$$

1.4 RESULTS

Descriptive Statistics

Table 2 presents data related to the distribution of the forecasts characteristics.

[INSERT TABLE 2 HERE]

Panel A shows that the vast majority of annual forecasts are issued with a range format (74.88%), 12.86% of the observations are qualitative forecasts and 10.31% are numerical point estimates, while only 1.95% are open-ended. Panel B shows that the management forecasts at minimum provide the earnings projection (lev. 0 disaggregation), more than half of the sample provide the revenue or sale item information (lev. 1 disaggregation), 18.29% accompany earnings with at least one major expense line item (lev. 2 disaggregation), while only 3.09% show more detailed line items (lev. 3 disaggregation). Panel C gives some information about the additional qualitative information. One quarter of the forecasts in the sample is bounded with CEO or CFO comments; almost 15% provide an explanation for the earnings estimate (of which 43.82% rely on internal attributions, while 37.08% on external attributions). Finally, 33.48% could be referred to as an earnings estimate update.

Table 3 reports data related to the distribution of the consistency measures.

[INSERT TABLE 3 HERE]

Panel A reveals that 11.12% of the observations are consistent at the strong level, 25.5% at the semi-strong level and 18.77% at the weak level. Panel B shows that, in terms of individual measures, 47.15% of the sample is consistent in precision, 35.54% is consistent in disaggregation and 20.46% is consistent in the type of additional information provided.

Table 4 illustrates the distribution of the sample and measures of consistency by industry.

[INSERT TABLE 4 HERE]

Panel A shows that the majority of observations belong to "other industry"[9] (16.87%), followed by retail (16.39%) and healthcare (15.19%). Panel B confirms the industry distribution for precision. The manufacturing, healthcare and retail industries are the most disaggregated at the revenues/sales level; the consumer non-durable and healthcare sectors display the most disaggregation at the major expenses level; the most disaggregated forecasts in terms of detailed line items level pertain to manufacturing firms. Panel C reports trends for the consistency measures. The semi-strong measure of consistency is prevalent for most of the sectors, except for the consumer durables which sees a prevalence of weak consistency. Among the individual measures, consistency in precision is generally the most prevalent followed by consistency in disaggregation.

Table 5 presents the distribution of the sample and measures by year.

[9] I decide to keep financial institutions in the sample given their number in order not to lose too many observations.

[INSERT TABLE 5 HERE]

Panel A depicts a clear trend: most of the observations pertain to the first half of the sample years, which accounts for over 70% of the total number of observations. Indeed, there exist evidence supporting a decreasing trend in earnings forecast issued after 2008.[10] Also, the sample selection criteria and the source from which forecasts are extracted (*Factiva* press releases) contribute to justify such a distribution. Reasonably, when the data collection started, Factiva might not have been updated with the full press releases coverage, especially of recent years (e.g. 2012-2013). Drawing the data from alternative available sources of earnings forecasts, such as "IBES Guidance", would have not allow the extensive collection of attributes given the different and limited nature of the data provided.

Panel B confirms the distribution of the characteristics by year. It shows a disproportioned amount of guidance bounded with CEO comments in 2005 and with update in 2006 and 2007. Panel C confirms the distribution of consistency measures by year with a prevalence of semi-strong consistency and consistency in precision over the years.

Table 6 summarizes the descriptive statistics for the set of regression variables.

[INSERT TABLE 6 HERE]

The distributions of the control variables are consistent with previous literature (Feng and Koch, 2010). On average, firms tend to be profitable (incurring losses are only 5% of the sample). Almost 60% report bad news and disclose the earnings estimates on average 5 days before the earnings announcements. Managers spend on average 16% of their lives in the CEO position.

Table 7 reports Pearson correlations.

---

[10] Ciconte et al. (2013) document a decrease from 2008 to 2010 in their earnings forecast sample collected from the CIG database. Also, a comparison with data obtained from the IBES-guidance database confirms that from 2009 earnings forecasts issuance drops to 8% compared to the average 12% in the years 2004-2008.

[INSERT TABLE 7 HERE]

Empirical Results for H1

To test the first hypothesis, I examine whether firm's and industry's specific factors are associated with the level of earnings forecasts consistency (proxied by *CONS_LEV*). The coefficients β_{it} represents the effect of each factor on the probability that a management earnings forecast is consistent either at a *weak*, *semi-strong* or *strong* level, relative to the probability that it reports no consistency. Table 8 shows the results.

[INSERT TABLE 8 HERE]

Results are consistent with a significant positive association between the experience of the CEO and the likelihood of reporting a higher level of consistency. The estimates of coefficient β_1 are positive across the two models with a value of 0.042, and significant at the 1 percent level. This corroborates the idea that the more experienced a CEO is, more likely she will be to provide highly consistent forecasts. Results also show that the coefficients on both *EARN_DIFF* and *L_SALE* are positive and significantly associated to the level of consistency, with values ranging from 0.002 to 0.397, all significant at the 1 percent level. The sign of these coefficients is not predictable *ex-ante*, however it suggests that the magnitude of the earnings surprise from one year to the next positively affects the decision to provide guidance cosistent at a certain level, as well as confirms that bigger firms are more likely to stick to previous disclosed chracteristics. Finally, the estimate of coefficient β_2 is negative and significant, with a value of – 1.414 suggesting that industry competition (concentration) positively (negatively) influences the probability of reporting a number of consistent characteristics. Table 8 also shows that the pseudo R^2 of the two models ranges from 6.2 to 6.4 percent and the sign of the coefficient for the control variables are in line with expectations based on previous literature. The sign of *ERR* suggests that firms that generally issue optimistic forecasts are relatively more likely to issue consistent forecasts as well. *FOLLOW* is positive, suggesting that firms may foster future analyst coverage and institutional participation by releasing earnings forecasts that report consistent characteristics, thus providing aid to external actors and allowing them to familiarize with the “forecast’s look”. The control variable signaling information uncertainty, *DISP*, exhibits negative sign. This supports the idea that managers facing firm-specific uncertainty are discouraged to committ to sticky policies of forecasts’ characteristics, and therefore less likely to keep issuing consistent guidance. The coefficients of *MEET* is negative although not significant.

Note that when the base model (Model 1) is augmented with LAG_$CONS_CHAR_{it}$ (Model 2), the coefficient β_{15} loads positively and significantly with a value of 0.932 reinforcing the idea that corporate disclosure policies are path dependent (Tang, 2012), not only in terms of presence or absence of a forecasts but even in their essence, thus it adds a novel piece to the puzzle.

Overall these results suggest that among the factors identified as determinants of single-period guidance characteristic, the experience of the CEO, the industry concentration index as well as the earnings surprise and the firm’s size more likely contribute to explain the stickiness of forecasts characteristics measured from a level-based perspective.

Empirical Results for *H2*

To probe further into whether some firm’s and industry’s specific characteristics are associated with consistency, I develop a second regression design aimed to discriminate among individual characteristics. I run a multinomial logistic regression with consistency in individual characteristics (*CONS_CHAR*) as the dependent variable. The specification of *CONS_CHAR* is now a categorical variable, with “0” as the comparison group (probability that the earnings forecast exhibits no consistency). Table 9 reports tabulated results.

[INSERT TABLE 9 HERE]

Results in Panel A are consistent with a significant positive association between the earnings surprise (*EARN_DIFF*) and the likelihood of being consistent in precision. The estimates of β_4 are positive across the two models, and significant at the 5 percent level. Results suggests that firm's size also plays a role in determining the likelihood of having consistent forecasts in precision. The coefficient on *L_SALE* is positive and strongly significant, ranging from 0.524 to 0.526. As in the previous test, when the proxy for lagged consistency, *LAG_CONS_CHAR*, is included in the model it loads positively and significantly (1 percent level) with a coefficient of 13.538, once again confirming that, when disclosing, firms make an implicit commitment to the market to provide similar disclosures in the future. Consequentially, among the determinants of guidance consistency, the historical pattern of characteristics is a key one.

Panel B shows the main determinants of consistency in disaggregation. The estimates for β_{3},β_5 and β_6, the coefficients respectively on *LIT*, *CAR* and *L_DAYS*, report negative and significant associations with the likelihood of being consistent in disaggregation from period to period. If a firms faces higher litigation risk, higher cumulative abnormal returns and greater uncertainty it is less likely to mantain the disclosure policy on disaggregation unchanged, instead allowing for fluctuations in the specification of this characteristic. This is in line with finding from previous literature regarding the level of disaggregation (Merkley et al. 2013). Managers rely on disaggregation, thus providing detailed forecasts of the income statement line items, to shed light on how they plan to achieve their bottom-line earnings. This practice is so specific and beneficial as well as risky, especially in presence of proprietary costs. Reasonably, in presence of higher litigation risks and uncertainty, which make earnings and other line items more difficult to forecast, a firm is more likely to sacrifice consistency for information witholding. Results are also consistent with a positive and significant association between FOLLOW and consistency, with a coefficient of 0.070, significant at the 1 percent level. This is in line with managers relying on consistency in order to help stakeholders to familiarize with the forecasts form, and analysts positively reacting to it. Note that, once again, firm's size and lagged consistency load positively and significantly.

Panel C reports the results for consistency in additional information. Resuls are consistent with a significant positive association between *CEO_EXP* and the likelihood of being consistent in providing additional information. The coefficient of β_1 is positive across the two models, and significant at the 1 percent level. The experience gained as CEO is one of the key determinants of the decision to continuously provide a certain type of qualitative information along with the earnings estimate. In addition, both the coefficients on *EARN_DIFF* and *L_DAYS* load positively and significantly, supporting a positive influence of the earnings surprise and the level of uncertainty in the firm's environment. Size loads positively and is significant at the 1 percent level. When adding the lagged consistency variable, it shows a positive and significant association.

In sum the results suggest that among the factors responsible for the consistent behavior of earnings forecasts at the individual characteristic level, firm's size is a common determinants for all the characteristics specifications. In addition, consistency in precision is driven by the earnings surprise. Consistency in disaggregation is influenced by litigations risk, uncertainty and the analysts covering a company, while consistency in the type of additional information provided with the earnings estimate depends primarily on the experience accumulated by the CEO and the level of uncertainty permeating firms' environment.

1.5 ADDITIONAL ANALYSIS

In this section, I conduct additional tests aimed to answer further questions that stem from the results of the main analysis. Management earnings forecasts' consistency has been defined as persistence of a set of/single characteristics over time, assuming that the benchmark for current guidance characteristics decision is firm's own past guidance history. Consistency, in its own nature, can effectively exercise a positive influence on the level of information asymmetry beyond the action of guidance release, leading to a better aligment between firms' private information and the market. In fact, providing forecasts with identical attributes aids analysts and investors in the understanding of the estimates content, while reducing their information processing cost. Following this line of thought, an interesting logical prosecution of this work is to explore whether managers consciously change forecast characteristics after a pattern of consistent guidance and whether there is some degree of alignment with previous tests while employing the same set of determinants.

More precisely, I examine a subsample of guidance including those presenting deviations from the historical pattern of characteristics and assume that a change in earnings forecasts' characteristics contributes to either a positive or negative change in the level of information asymmetry. Given that a break in a consistent pattern of forecasts' characteristics occurs, this test aims to investigate why it is most likely to happen.

I run a multinomial logistic regression and use *BREAK_CONS* as the dependent variable. Note that *BREAK_CONS* is a categorical variable that takes the value of "0" when no breaks are reported (comparison group), "1" if a break in precision is reported, "2" if a break in disaggregation is reported and "3" if a break in additional information is reported. The model is as follows:

$$\begin{aligned} BREAK\_CONS_{it} = {} & \beta_0 + \beta_1\, CEO\_EXP_{it} + \beta_2\, HH_{it} + \beta_3\, LIT_{it} + \beta_4\, EARN\_DIFF_{it} + \beta_5\, CAR_{it} + \\ & + \beta_6\, L\_DAYS_{it} + \beta_7\, BAD\_NEWS_{it} + \beta_8\, ERR_{it} + \beta_9\, FOLLOW_{it} + \beta_{10}\, DISP_{it} + \\ & + \beta_{11}\, MEET_{it} + \beta_{12}\, ROA_{it} + \beta_{13}\, L\_SALE_{it} + \beta_{14}\, LEV_{it} + \varepsilon. \end{aligned} \tag{1}$$

Table 10 reports tabulated results.

[INSERT TABLE 10 HERE]

Results are consistent with a positive and significant association between *CAR* and the likelihood of breaking a consistent pattern of guidance precision. The estimates of the coefficients on *LIT* and *DISP* are also positive and significant, highlighting a positive infuence of both litigation risk and uncertainty of the information environment on the probability to deviate from a consistent pattern of earnings forecast precision.

The results for breaks in disaggregation are consistent with a negative and significant effect of both *CEO_EXP* and *EARN_DIFF*, althought the latter is very small in magnitude.

Finally, results for breaks in qualitative additional information suggest a positive effect of litigation risk, cunulative abnormal returns and uncertainty, all loading positively and strongly significantly. Surprisingly, the coefficient on *FOLLOW* is negative and significant.

Although, these results provide interesting insights while adding to a deeper understanding of guidance patterns violation, their interpretation as symmetric outcomes relative to previous tests (breaks could indeed represent the opposite phenomenon) is doubtful. Althought the sample in question is limited to management earnings forecasts that have been released with a certain degree of consistency, the definition of breaks does not allow to discriminate between positive (deviation to a higher level of detail) VS negative breaks (deviation to a lower level of detail), which could cotnribute to off-set the results. I plan to address this issue in future version of the paper, by running separate regressions that consider each "break type" searately.

1.6 CONCLUSIVE REMARKS

Prior studies suggest different rationale behind managers' decision to issue earnings forecasts as well as to change or stop them, but in general lack a multi-period approach. The very few adopting a dynamic approach do not provide evidence about patterns of earnings forecasts characteristics and their determinants. Indeed, managers have a lot of discretion. They not only decide the timing and the informative content of disclosure but also its "inner" characteristics. To this respect, the examination of forecast characteristics and their role as part of a wider disclosure strategy is still an open question.

Bridging together these researches, the paper aims at empirically testing the role of the main determinants identified in the literature in explaining patterns of forecasts characteristics.

Building on previous literature on guidance characteristics, I focus on a new definition of consistency based on precision, level of disaggregation and additional qualitative information. I classify firm as “consistent” if a set of characteristics (or the individual characteristic) persists over time remaining unchanged.

Preliminary results suggest that among the identified variables, the experience of the CEO, the industry concentration as well as the firm’s size more likely contribute to explain the stickiness of forecasts characteristics measured from a level-based perspective. More experienced managers reserve attention to additional details of guidance and are inclined to maintain forecasts characteristics either to aid stakeholders providing them with a familiar base of attributes to interpret the earnings estimates, or to signal their managerial style. On the other side, bigger firms in less concentrated, thus more competitive, industry are more likely to develop consistent characteristics policies.

In addition, the results suggest that among the factors responsible of earnings forecasts consistency at the individual characteristic level, firm’s size is a common determinant for all the three characteristics specifications. Consistency in precision is mainly driven by the earnings surprise, which can be assumed to be related to performance. Consistency in disaggregation is influenced by litigations risk, the level of uncertainty and the number of analysts following a company, while consistency in the type of additional information provided with the earnings estimate depends primarily on the experience accumulated by the CEO and the level of uncertainty permeating firms’ environment.

The paper contributes to the current debate on guidance practice. It suggests that above and beyond the measure of guidance frequency (that consider the mere existence of a forecast), the study of the inner characteristics of earnings forecasts in a multi-period perspective especially deserves attention, given that managers have greater discretion over their choice and analysts' behavior may be influenced by them. The evidence presented in the paper should be of interest to academics who study corporate voluntary disclosure, as well as to practitioners and managers who are responsible of firms' disclosure policies.

APPENDIX

Variable Definitions

Consistency measures

CONS_LEV = *ordinal variable that takes the value of "0" if the earnings forecast displays no consistency (comparison group), "1" if the forecast reports a weak consistency, "2" if the forecast reports a semi-strong consistency and "3" if the forecast reports a strong level of consistency.*

CONS_CHAR =*categorical variable that takes the value of "0" if the earnings forecast displays no consistency (comparison group), "1" if the forecast is consistent in precision, "2" if the forecast is consistent in disaggregation and "3" if the forecast is consistent in the additional qualitative information.*

BREAK_CONS = *categorical variable that takes the value of "0" when no breaks are reported, "1" if a break in precision is reported (comparison group), "2" if a break in disaggregation is reported and "3" if a break in additional information is reported.*

Managers' specific characteristic

CEO_EXP = *total years accumulated as CEO*

Industry Competition

HH = *Herfindal index, the sum of squared product market shares of firms in the industry (48 Fama–French industry groupings). The higher the index, the lower competition.*

Litigation

LIT = *indicator variable equal to 1 for whether the firm is in a high-litigation industry (SIC codes: 4812–4813, 4833, 4841, 4811–4899, 4922–4924, 4931, 4941, 6021–6023, 6035–6036, 6141, 6311, 6321, 6331)*

Guidance motivation variables

BAD_NEWS = *indicator variable equal to 1 if the company's earnings are lower than the most recent analyst consensus from the IBES summary data before the disclosure event, 0 otherwise.*

ERR = *average error of the forecasts issued by the firm relative to the earnings that is being currently announced (i.e. the earnings of year t), scaled by price. Error is calculated as forecasted earnings less actual earnings.*

MEET = *indicator variable equal to 1 if realized annual EPS is greater than or equal to analysts' consensus forecasts in year t, 0 otherwise*

Market Reaction

CAR = *absolute value of firm's three day size-adjusted return centered on the issuance date of the earnings announcement.*

Uncertainty

L_DAYS = *logarithm of the calendar days between the earnings forecast issuance date and the earnings announcement date.*

DISP = *standard deviation of analysts' EPS forecasts for year t in the most recent consensus from the IBES summary data*

Earnings Surprise

EARN_DIFF*= difference between realized EPS in year t-1 and realized EPS in year t scaled by realized EPS in year t.*

Other Control variables

ROA *= return on assets in year t*

L_SALE *= natural log of total sales in year t*

LEV *= ratio of total debt over total assets at the end of year t-1.*

Figure 1: Classification scheme

	MEF TIME				MEF PRECISION				DISAGGREGATION				ADDITIONAL INFO			
MEF CODE	ISSUANCE DATE	FY	QUARTER	ANNUAL	POINT	RANGE	OPEN-ENDED	QUALITATIVE	LEV 0 (EPS)	LEV 1 (SALES)	LEV 2 (EXP)	LEV 3 (OTHER)	EPS INTERNAL EXPLAN.	EPS EXTERNAL EXPLAN.	UP DATE	CEO/CFO COMMENT
OBS 1 to 5434	Date of mef issuance	Fiscal year of reference	Quarter of reference (1,2,3)	0-1 if refers to quarter 4 (annual)	earnings are forecasted as a point value	earnings are forecasted in a range of values	earnings are forecasted as a max or min value	earnings are forecasted using a qualitative statement	mef reports EPS or net income	mef reports: sales, revenues, comparable store sales, organic sales	mef reports: inventory, CF, free CF, cash, recurring cost, recurring expense, costs of goods sold, gross margin, R&D, selling exp., general exp., capital exp., administrative exp., depreciation, interest exp., effective tax rate, income tax rate	mef reports: amortization exp., other recurring exp. items, other exp.	mef explains forecasted earnings with internal attribution	mef explains forecasted earnings with external attribution	mef is an update	mef reports also a CEO/CFO comment on expected earnings

Table 1. Examples of Consistency

	T			**T+1**		
Definitions of Consistency (Examples)	*PRECISION*	*DISAGGREGATION*	*ADDITIONAL QUALITATIVE INFO*	*PRECISION*	*DISAGGREGATION*	*ADDITIONAL QUALITATIVE INFO*
WEAK		X			X	
SEMI-STRONG	X		X	X		X
STRONG	X	X	X	X	X	X
CONS IN PREC.	X			X		
CONS IN DISAG.		X			X	
CONS IN ADD. INFO			X			X

Table 2. Distribution of the Characteristics: precision, disaggregation and additional information

Panel A

By precision	**Frequency**	**Percent**
Point	190	10.31
Range	1,380	74.88
Open End	36	1.95
Qualitative	237	12.86
Total	1,843	100

Panel B

By disaggregation	**Frequency**	**Percent**
Level 0	1,843	100
Level 1	1,004	54.48
Level 2	337	18.29
Level 3	57	3.09
Total	1,843	-

Panel C

By additional information	**Frequency**	**Percent**
Earnings Explanation	267	14.49
Internal Attribution	*117*	*43.82*
External Attribution	*99*	*37.08*
Both	*47*	*17.6*
CEO/CFO comment	475	25.77
Update	617	33.48
Total	1,843	-

Table 3. Distribution of the consistency measures: level-based and characteristic-based

Panel A

By consistency (level)	Frequency	Percent
Strong	205	11.12
Semi-strong	470	25.5
Weak	346	18.77
No consistency	822	44.6
Total	1,843	100

Panel B

By consistency (individual)	Frequency	Percent
Precision	869	47.15
Disaggregation	655	35.54
Additional info	377	20.46
Precision, disaggregation, additional info	205	11.12

Table 4. Distribution of observations, characteristics and measures of consistency by industry

Panel A

By industry	**Frequency (Obs.)**	**Percent**
Consumer Non-Durables	224	12.15
Consumer Durables	73	3.96
Manufacturing	267	14.49
Energy	45	2.44
Hi-Tech	207	11.23
Telecom	25	1.36
Shops/Retail	302	16.39
Healthcare	280	15.19
Utilities	109	5.91
Other (finance included)	311	16.87
Total	1,843	100

Panel B

	Precision				Disaggregation				Additional Qualitative Information				
Industry	**Point**	**Range**	**Open**	**Qual.**	**Lev 0**	**Lev 1**	**Lev 2**	**Lev 3**	**Eps explanation**	**Internal**	**External**	**CEO comm.**	**Update**
Consumer Non-Durables	15	169	15	18	224	109	73	7	32	22	15	67	86
Consumer Durables	2	58	0	10	73	41	26	1	13	8	6	24	28
Manufacturing	34	214	2	24	267	179	43	12	45	27	26	79	91
Energy	3	22	1	20	45	18	21	8	14	3	13	9	13
Hi-Tech	26	154	3	28	207	144	19	5	24	18	14	53	58
Telecom	5	17	2	6	25	15	5	1	4	1	3	4	5
Shops/Retail	26	240	1	36	302	148	29	6	28	14	16	66	114
Healthcare	19	218	2	31	280	174	66	7	34	20	20	57	90
Utilities	8	98	0	4	109	6	15	4	15	9	7	22	31
Other (finance included)	48	195	12	57	311	126	32	4	49	36	22	78	83
Total	**186**	**1,385**	**38**	**234**	**1,843**	**960**	**329**	**55**	**258**	**158**	**142**	**459**	**485**

Panel C

Industry	Strong cons.	Semi-strong cons.	Weak cons.	Cons. (Precision)	Cons. (Disaggreg.)	Cons. (Add. Info)	Break (precision)	Break (disaggreg.)	Break (Add. Info)
Consumer Non-Durables	33	65	65	139	99	58	39	25	30
Consumer Durables	7	17	26	44	22	12	13	7	7
Manufacturing	27	80	59	135	106	48	45	28	25
Energy	3	10	10	22	11	6	5	4	1
Hi-Tech	16	37	25	63	54	30	28	9	10
Telecom	2	5	3	5	7	4	3	0	3
Shops/Retail	36	85	45	152	108	71	52	25	27
Healthcare	36	74	54	149	98	74	42	22	23
Utilities	17	32	14	51	48	21	27	2	5
Other (finance included)	28	65	45	109	102	53	56	19	14
Total	**205**	**470**	**346**	**869**	**655**	**377**	**310**	**141**	**145**

Table 5. Distribution of observations, characteristics and consistency by year

Panel A

By year	Frequency	Percent
2004	29	1.57
2005	365	19.8
2006	424	23.01
2007	293	15.9
2008	230	12.48
2009	139	7.54
2010	124	6.73
2011	114	6.19
2012	119	6.46
2013	6	0.33
Total	1,843	100

Panel B

Year	Precision				Disaggregation				Additional Qualitative Information				
	Point	**Range**	**Open**	**Qual.**	**Lev 0**	**Lev 1**	**Lev 2**	**Lev 3**	**Eps explanation**	**Internal**	**External**	**CEO comm.**	**Update**
2004	5	10	0	14	29	14	1	0	5	6	2	7	14
2005	43	270	2	50	365	179	44	6	55	40	30	153	57
2006	47	326	6	45	424	208	50	4	61	40	32	90	133
2007	23	232	3	35	293	172	55	7	31	22	11	39	124
2008	23	171	12	24	230	147	47	7	20	10	12	30	93
2009	11	106	3	19	139	70	43	6	34	15	22	47	61
2010	12	85	6	21	124	76	32	11	21	9	12	37	34
2011	9	91	2	12	114	75	32	7	21	13	11	29	50
2012	17	84	2	16	119	61	31	9	18	8	14	40	50
2013	0	5	0	1	6	2	2	0	1	1	0	3	1
Total	**190**	**1380**	**36**	**237**	**1843**	**1004**	**337**	**57**	**267**	**164**	**146**	**475**	**617**

Panel C

Year	**Strong cons.**	**Semi-strong cons.**	**Weak cons.**	**Cons. (Precision)**	**Cons. (Disaggreg.)**	**Cons. (Add. Info)**	**Break (precision)**	**Break (disaggreg.)**	**Break (Add. Info)**
2004	6	4	3	13	9	7	0	3	4
2005	28	56	37	106	82	45	26	23	23
2006	34	113	68	187	138	71	66	25	28
2007	53	74	56	150	128	85	57	30	38
2008	33	64	39	115	90	61	52	17	22
2009	9	42	41	77	49	26	24	13	12
2010	17	37	31	72	55	29	26	16	12
2011	14	38	30	70	51	27	33	10	6
2012	9	39	40	74	48	23	43	4	2
2013	2	3	1	5	5	3	4	0	0
Total	**205**	**470**	**346**	**869**	**655**	**377**	**331**	**141**	**147**

Table 6: Descriptive Statistics

	N. 1843						
Variable	Mean	SD	Min	0.25	Median	0.75	Max
CEO_EXP	9.73	7.22	0.52	5.09	8.02	12.42	39.52
HH	0.25	0.19	0.02	0.11	0.19	0.32	1.00
LIT	0.22	0.42	0.00	0.00	0.00	0.00	1.00
EARN_DIFF	-74.16	159.60	-454.00	-102.00	-15.43	9.34	100.84
CAR	0.06	0.06	0.00	0.02	0.04	0.09	0.27
L_DAYS	5.08	0.84	2.40	4.59	5.46	5.76	5.89
BAD_NEWS	0.58	0.49	0.00	0.00	1.00	1.00	1.00
ERR	0.00	0.18	-1.01	-0.01	0.01	0.05	0.60
FOLLOW	11.38	7.05	1.00	5.00	10.00	16.00	30.00
DISP	0.05	0.08	0.00	0.01	0.02	0.05	0.57
MEET	0.75	0.43	0.00	0.00	1.00	1.00	1.00
ROA	0.05	0.11	-0.54	0.03	0.06	0.10	0.30
L_SALE	7.76	1.88	-2.42	6.53	7.90	9.09	13.01
LEV	0.18	0.16	0.00	0.04	0.15	0.28	0.72

Table 7. Pearson Correlations between the variables

Variable Name	1)	2)	3)	4)	5)	6)	7)	8)	9)	10)	11)	12)	13)	14)	15)	16)	17)	18)	19)
1) CONS_LEV	1																		
2) CONS_CHAR	0.9413*	1																	
3) BREAK	0.6181*	0.6131*	1																
4) CEO_EXP	0.0447	0.0432	0.0169	1															
5) HH	0.0268	0.033	0.0549*	-0.0690*	1														
6) LIT	0.0304	0.0347	0.0399	-0.0775*	-0.1346*	1													
7) EARN_DIFF	-0.039	-0.0541*	-0.0348	0.0794*	-0.0496*	-0.0022	1												
8) CAR	-0.0712*	-0.0813*	-0.008	-0.0042	0.027	-0.0033	0.1178*	1											
9) L_DAYS	0.0273	0.0412	0.0356	-0.0229	-0.0094	0.0047	0.0174	-0.0353	1										
10) BAD_NEWS	-0.0455	-0.0387	-0.0544*	0.0006	0.0164	-0.0757*	0.1533*	0.0548	0.0876*	1									
11) ERR	0.0103	0.0105	0.0213	0.0483	-0.0377	0.0316	-0.1008*	-0.0154	-0.0025	-0.2070*	1								
12) FOLLOW	0.1050*	0.1320*	0.0590*	-0.1283*	-0.0423	0.3243*	-0.3736*	-0.1406*	-0.042	-0.1019*	0.1029*	1							
13) DISP	-0.0174	-0.0126	0.0103	0.0909*	-0.0504*	-0.0701*	0.004	0.0196	0.0366	0.1131*	-0.0861*	-0.0713*	1						
14) MEET	-0.0076	0.0063	-0.0023	-0.0163	-0.0126	0.0675*	-0.0963*	-0.0338	-0.0086	-0.1868*	0.5210*	0.1394*	-0.0863*	1					
15) LAG_CONS_LEV	0.1379*	0.1445*	0.0493*	-0.0206	0.0276	0.0276	-0.0780*	-0.0652	0.0191	-0.0465*	-0.0099	0.0536*	0	-0.0351	1				
16) LAG_CONS_CHAR	0.4068*	0.3669*	0.1668*	0.021	0.029	0.0305	-0.0797*	-0.0862*	0.0139	-0.1057*	0.0157	0.1385*	-0.0059	-0.0079	0.3533*	1			
17) ROA	0.0650*	0.0618*	0.0532*	0.0309	0.0906*	0.1219*	-0.1947*	-0.0548	-0.0361	-0.1935*	0.1481*	0.2375*	-0.2648*	0.1819*	0.0358	0.0685*	1		
18) L_SALE	0.1655*	0.1657*	0.1123*	-0.2087*	0.0549*	0.1656*	-0.4280*	-0.2261*	-0.0347	-0.1502*	0.1034*	0.5898*	0.0798*	0.1248*	0.0712*	0.1621*	0.2353*	1	
19) LEV	0.0131	-0.0024	0.0166	-0.0530*	-0.0236	-0.1371*	0.041	0.0071	0.0198	0.0357	0.027	-0.0971*	0.1218*	-0.0298	0.0071	-0.0251	-0.1882*	0.1327*	1

Table 8: Determinants of level-based consistency (Equations 1 and 1a)

	Exp. sign	*Dep. Var: CONS_LEV* Model 1	Model 2
CEO_EXP	?	0.042***	0.042***
		(3.10)	(3.17)
HH	?	-1.414**	-1.418**
		(-2.32)	(-2.34)
LIT	?	-0.206	-0.214
		(-0.83)	(-0.85)
EARN_DIFF	?	0.002***	0.002***
		(3.04)	(2.94)
CAR	?	-3.228	-3.068
		(-1.25)	(-1.19)
L_DAYS	?	-0.013	-0.021
		(-0.12)	(-0.20)
BAD_NEWS	?	0.040	0.033
		(0.19)	(0.16)
ERR	?	1.243	1.299
		(1.43)	(1.47)
FOLLOW	?	0.012	0.012
		(0.60)	(0.58)
DISP	?	-2.139	-2.207
		(-1.13)	(-1.15)
MEET	?	-0.012	-0.037
		(-0.04)	(-0.12)
ROA	?	2.558	2.365
		(1.37)	(1.26)
L_SALE	?	0.397***	0.386***
		(4.35)	(4.21)
LEV	?	-1.327	-1.299
		(-1.61)	(-1.58)
LAG_CONS_LEV	?		0.932***
			(2.34)
INTERCEPT		Included	Included
Pseudo-R2		0.062	0.064
Obs.		1,843	1,843
Wald Chi-sq		55.39	67.65
		p = 0.000	p = 0.000

Z-statistics are based on standard error estimates.
*** Statistical significance at the 0.01 level, using a two-tailed test.
** Statistical significance at the 0.05 level, using a two-tailed test.
* Statistical significance at the 0.10 level, using a two-tailed test.

Table 9: Determinants of characteristic-based consistency (Equations 2 and 2a)

	Panel A: CONS_PREC			*Panel B:CONS_DISAGG*			*Panel C: CONS_ADD*		
	Exp. sign	Model 3	Model 4	*Exp. sign*	Model 3	Model 4	*Exp. sign*	Model 3	Model 4
CEO_EXP	?	0.037	0.037	?	0.022	0.016	?	0.063***	0.064***
		(1.33)	(1.32)		(1.08)	(0.76)		(3.66)	(3.62)
HH	?	-1.412	-1.382	?	-1.226	-0.972	?	-1.529	-1.502
		(-1.10)	(-1.08)		(-1.45)	(-1.17)		(-1.62)	(-1.59)
LIT	?	0.231	0.240	?	-0.857**	-0.901**	?	0.141	0.142
		(0.49)	(0.51)		(-2.05)	(-2.01)		(0.42)	(0.43)
EARN_DIFF	?	0.003**	0.003**	?	0.002*	0.001	?	0.003**	0.002**
		(2.10)	(2.02)		(1.70)	(0.84)		(2.41)	(2.31)
CAR	?	4.159	-4.009	?	-8.454**	-6.947*	?	-0.403	-0.338
		(-0.94)	(-0.91)		(-2.17)	(-1.83)		(-0.12)	(-0.10)
L_DAYS	?	-0.196	-0.203	?	-0.314**	-0.293**	?	0.411**	0.410**
		(-0.86)	(-0.89)		(-2.22)	(-2.01)		(2.28)	(2.28)
BAD_NEWS	?	0.250	0.238	?	0.063	0.024	?	-0.026	-0.026
		(0.53)	(0.51)		(0.21)	(0.08)		(-0.08)	(-0.08)
ERR	?	1.368	1.287	?	1.143	1.660	?	2.293	2.255
		(0.58)	(0.53)		(1.08)	(1.55)		(1.25)	(1.22)
FOLLOW	?	0.010	0.009	?	0.071***	0.070***	?	-0.032	-0.033
		(0.31)	(0.28)		(2.71)	(2.59)		(-0.99)	(-1.04)
DISP	?	-10.794	-10.447	?	1.015	0.865	?	-6.023	-5.969
		(-1.26)	(-1.23)		(0.54)	(0.46)		(-1.27)	(-1.26)
MEET	?	0.156	0.143	?	0.140	0.044	?	-0.112	-0.124
		(0.22)	(0.20)		(0.32)	(0.10)		(-0.25)	(-0.28)
ROA	?	4.907	4.882	?	0.714	-0.380	?	4.475*	4.438*
		(1.52)	(1.51)		(0.22)	(-0.12)		(1.81)	(1.79)
L_SALE	?	0.526***	0.524***	?	0.292**	0.206*	?	0.520***	0.522***
		(3.24)	(3.17)		(2.45)	(1.71)		(3.50)	(3.43)
LEV	?	-2.685*	-2.657*	?	-1.395	-0.971	?	-1.570	-1.562
		(-1.78)	(-1.76)		(-1.11)	(-0.77)		(-1.40)	(-1.39)
LAG_CONS_CHAR	?		13.538***	?		15.633***	?		13.309***
			(11.57)			(32.19)			(16.32)
INTERCEPT		Included	Included		Included	Included		Included	Included
Pseudo-R2		0.106	0.128		0.106	0.128		0.106	0.128
Obs.		1,843	1,843		1,843	1,843		1,843	1,843
Wald Chi-sq		110.55	1824.92		110.55	1824.92		110.55	1824.92
		p = 0.000	p = 0.000		p = 0.000	p = 0.000		p = 0.000	p = 0.000

Z-statistics are based on standard error estimates.
*** Statistical significance at the 0.01 level, using a two-tailed test.
** Statistical significance at the 0.05 level, using a two-tailed test.
* Statistical significance at the 0.10 level, using a two-tailed test.

Table 10: Determinants of breaks in consistency (Equations 3)

	Exp.	*Dep. Var.: BREAK_CONS*		
	sign	*Break_prec*	*Break_disagg*	*Break_add*
CEO_EXP	?	-0.021	-0.057***	0.019
		(-0.65)	(-2.63)	(0.74)
HH	?	3.185	-2.734	1.819
		(-1.25)	(-0.98)	(0.81)
LIT	?	1.251*	-0.583	1.668**
		(1.84)	(-0.47)	(2.54)
EARN_DIFF	?	-0.006**	-0.004**	-0.001
		(-2.55)	(-2.27)	(-0.41)
CAR	?	13.997**	6.959	13.009**
		(2.01)	(0.96)	(2.17)
L_DAYS	?	0.128	-0.046	0.939***
		(0.37)	(-0.14)	(2.65)
BAD_NEWS	?	-0.958*	-0.244	-0.415
		(-1.69)	(-0.37)	(-0.67)
ERR	?	-5.017	1.520	5.324
		(-1.15)	(0.48)	(1.52)
FOLLOW	?	-0.070	-0.045	-0.189***
		(-1.37)	(-0.51)	(-3.33)
DISP	?	13.705***	-2.570	-5.252
		(2.72)	(-0.22)	(-0.38)
MEET	?	0.469	-0.758	-0.620
		(0.60)	(-0.80)	(-0.74)
ROA	?	-2.491	-5.033	12.618*
		(-0.54)	(-0.92)	(1.95)
L_SALE	?	-0.638*	-0.036	0.548*
		(-1.90)	(-0.11)	(1.94)
LEV	?	3.512	1.025	5.237**
		(1.50)	(0.34)	(2.09)
INTERCEPT		Included	Included	Included
Pseudo-R2		0.221	0.128	0.106
Obs.		1,021	1,021	1,021
Wald Chi-sq		72.36	72.36	72.36
		p = 0.000	p = 0.000	p = 0.000

Z-statistics are based on standard error estimates.
*** Statistical significance at the 0.01 level, using a two-tailed test.
** Statistical significance at the 0.05 level, using a two-tailed test.
* Statistical significance at the 0.10 level, using a two-tailed test.

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CHAPTER 2

Consequences of Management Earnings Forecast Consistency

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Consequences of Management Earnings Forecast Consistency

ABSTRACT

This paper investigates the effects of consistent disclosure of management earnings forecast characteristics on the information environment. Building on previous literature on guidance characteristics, I focus on a new measure of consistency based on three attributes: precision, level of disaggregation and additional qualitative information. I classify firms as "consistent" based on persistence of characteristics over time, and exploit two different settings: one to test the incremental level of consistency (firm-based consistency) and the other to test consistency at the individual level. The paper studies management earnings forecasts' consistency from a longitudinal perspective to examine its effect on the properties of financial analysts, while previous studies on dynamic disclosure only assess the extent to which firms' behavior in the past affect the likelihood of providing voluntary disclosure in the future. Preliminary results suggest that a strong level of consistency positively affects a firm's information environment, helping analysts to align their expectations with managers. When looking at individual consistent characteristics, the positive effect on analysts dispersion seems to be driven by all the three characteristics but with a larger impact of consistency in precision. Accuracy is positively influenced by consistency in the level of disaggregation, while analyst coverage increases are attributable to the level of precision being unchanged from year to year.

Keywords: Management Earnings Forecasts, Consistency, Characteristics, Financial Analysts Properties

Data Availability: Data used in this study are available from public sources indicated in the text.

2.1 INTRODUCTION

Voluntary disclosure has been a major theme in accounting and management earnings forecast is the most common form. Companies rely on this disclosure to communicate financial performance expectations to stakeholders. King et al. (1990) define earnings forecasts as "*voluntary disclosures predicting earnings prior to the expected reporting date for a given firm*".

Existing research largely focus on why managers issue forecasts and the consequences of this decision (Ajinkya and Gift 1984; Skinner 1994; Stocken 2000; Verrecchia 2001), but few studies examine how managers choose the characteristics[11] of earnings forecasts (Hirst et al., 2008). From managers' perspective earnings forecasts are mainly issued to align market participants' expectations of the firm's earnings with their own expectations (Ajinkya and Gift 1984), thus reducing information asymmetry. Self-interested managers may disclose private information in order to influence investors' assessment of their ability to anticipate future changes in the firm's economic environment (Trueman, 1986). Forecasts also represent a voluntary disclosure mechanism by which managers alter market earnings expectations and strategically address stakeholders' impressions of firm performance (Yuthas et al. 2002; Bowen et al. 2005).

All these studies implicitly assume that the release of earnings forecast is an important tool to analysts and investors as they are engaged in strategic analysis in order to assess firm's value. However, the use and dissemination of information by analysts and stakeholders depends also on the form and qualitative attributes of the disclosure itself.

Despite the regulation requirements, managers have considerable discretion over the forecasting activity (Baginski et al., 2004). Managers not only decide the timing and the informative content of disclosure but also its "inner" characteristics.

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[11] As in Hirst et al. (2008), forecast characteristics are to be intended as properties or attributes of the earnings forecast *per se*.

Some empirical studies focus on the consequences of earnings forecast characteristics, testing stock price changes and analysts behavior (Baginski et al., 1993; Williams, 1996; Merkley et al., 2012; Lansford et al., 2013). Most of them, however, ignores the iterative nature of the forecasting activity, treating earnings forecasts as a single period decision. Only recently research has started examining time-series patterns of earnings guidance[12] and exploring their multi-period nature (Graham et al., 2005; Einhorn and Ziv, 2008; Tang, 2012).

A survey by Graham et al. (2005) points out that, when making guidance decisions, managers place increasing weight on being consistent with their past guidance, hence they work to maintain predictability in earnings and financial disclosure. Einhorn and Ziv (2008) introduce a multi-period analytical model to investigate the extent to which firms' strategic disclosure behavior in the past affects their propensity to provide voluntary disclosures in the future. Tang (2012) empirically tests consistency and finds that firms are more reluctant to deviate from their existing practice after a history of consistent guidance.

Stemming from this recent debate, I intend to investigate whether firms follow a consistent pattern of earnings forecasts characteristics and how this affects the information environment. In other words, I explore whether the activity of analysts is sensitive on the consistency of characteristics.

Using a sample of hand-collected management earnings forecasts for the period 2005-2013, I develop different measures of consistency considering three attributes: the earnings forecast precision, the level of disaggregation and the type of additional qualitative information. I classify firms as "consistent" based on persistence of characteristics over time. Consistency may refer to the number of characteristics that do not change from one period to the other, as well as to

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[12] I use the terms "earnings forecast" and "guidance" as interchangeable.

characteristics taken individually. The first measure is designed to capture the incremental level of consistency, while the second conveys insights into the specific role of a single attribute.

I test whether financial analyst's activity is sensitive to consistency in guidance characteristics. I estimate different OLS models, one for each analysts proxy (i.e. dispersion, accuracy and portion of analysts following), and regress them on the measures of consistency, plus a set of controls. Preliminary results suggest that the consistent disclosure of earnings forecast characteristics have to some extent a positive impact on the information environment. Although earnings forecasts are voluntary disclosed and managers may still act opportunistically providing forecasts with different levels of detail, analysts benefit from managers being consistent with past choices. In fact, by reiterating a commitment to past characteristics, while managers cannot alter the news itself, they can provide analysts with a familiar basis to interpret both favorable and unfavorable news.

To the best of my knowledge most of the existing research analyze firms' voluntary disclosure decisions within single-period settings and lack a multi-period approach to the study of earnings forecasts. The very few adopting a dynamic perspective do not consider the qualitative characteristics of the forecast, potentially missing an important information. Also, while recent research examines the negative consequences associated with interrupting a disclosure precedent (Houston et al., 2010; Chen et al., 2011), empirical evidence on the consequences of keeping certain characteristics unchanged is still absent. This paper makes an empirical contribution to the disclosure studies in the setting of management earnings forecast and introduces a new definition of consistency, which refers to persistence of guidance characteristics over time. I explore whether managers issue consistent earnings forecasts in terms of characteristics, whether financial analysts recognize consistent pattern of characteristics and how they react. Overall, I investigate from a longitudinal perspective earnings forecasts' characteristics and the relative effect on analysts activity, while previous literature on dynamic disclosure only assess the extent to which firms' strategic disclosure behavior in the past affects their prosperity to provide voluntary disclosures in the future.

As Baginski and Hassell (1997) point out: "*A greater understanding of managers' information production decisions is critical in addressing disclosure issues, especially with regard to voluntary, prospective information*". This paper suggests that the examination of the inner characteristics of earnings forecasts in a multi-period perspective especially deserves attention, given that managers have greater discretion over their choice and analysts' behavior may be influenced by them.

Many of the motivations managers have for releasing earnings forecasts are consistent with reducing the asymmetry in information between managers and analysts and current or potential investors (Ajinkya and Gift 1984; Verrecchia 2001). I also add to this stream of literature by providing evidence that consistency in forecats characteristics might contribute to keep the level of information asymmetry unchanged over time (given the different level of detail each attribute provides), thus benefiting shareholders' response to disclosure over time.

The study also adds to the recent literature examining firms that stop providing earnings guidance and demonstrates that changes in guidance patterns may not necessarily relate to the interruption of guidance itself, but could be analyzed at a finer level by peek into each document and examining its inner content.

Finally, the topic presented in this paper should be of interest to accounting researchers who study voluntary disclosure as well as to executives who make voluntary disclosure decisions.

The rest of the paper is organized as follows. Section 2 discussed the relevant research and outlines plausible predictions. Section 3 describes the data and the research design. Section 4 reports the results from the empirical tests. Section 5 discusses implications of the research.

2.2 THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

In this section, I introduce management earnings forecasts by providing a brief overview of the practice and its role. Then I turn to the theory and related empirical studies about the choice to provide earnings forecasts with specific characteristics and their effects.

Managers Earnings Forecasts at a glance and multi-period nature

Management forecasts represent an important form of corporate voluntary disclosure as it deals with future expectation about firms' performance. Research documents that forecasts have become a primary source of "value relevant" information and are valued by investors far more than other forms of disclosure (Rogers et al., 2009). Consequentially, there is significant demand from capital market participants for the disclosure of earnings forecasts (Healy and Palepu, 2001).

The forecasting practice dates back to the 1970s when managers began privately to convey information about firm value and prospects to big investors. The practice then grew until 2000, when Regulation Fair Disclosure was introduced and required all the information disclosed to be of public domain, thus avoiding the communication made in favor of particular categories of stakeholders. Public information is subject to scrutiny and managers commit themselves when issuing the first forecast. Analysts and investors are in fact engaged in strategic analysis in order to assess firm's value and are likely using prior forecasting behavior to assess current forecasts.

Managers have considerable discretion over the forecasting activity (Baginski et al., 2004). They not only decide the timing and the "news" of disclosure but even its "inner" characteristics. Bhojraj et al. (2011) argue that frequent guiders are more likely to spend greater time and effort on guidance, thus affecting their properties.

Nevertheless, there is still relatively limited research focusing on how managers choose forecast characteristics as compared to why managers decide to issue a forecast and the expected consequences of doing so. The paper extends this research providing evidence that, beyond the effects of single-period forecasts, the dynamic nature of their characteristics and the related effects on analysts’ activity is worth studying, given that current guidance sets a precedent that the market expects to continue in the future (Graham et al., 2005). More precisely, managers may decide to maintain forecast characteristics over time as to not influence market perception. Past guidance characteristics become the driver for present guidance (Tang, 2012), which leads to observe some degree of consistency from one period to the other. Although consistency of characteristics has not been tested by previous literature, Tang (2012) referring to the presence (or absence) of a given forecast in a given quarter or fiscal year, finds that 55% of the guidance patterns are consistent. Lansford et al. (2012) observe that almost 70% of disaggregating firms continue to disaggregate guidance in the following year.

With respect to the timing, a recent stream of research explores guidance frequency to summarize their trend, as well as the decision to stop providing guidance at a certain point in time. Rogers et al. (2009) study how management earnings forecasts affect stock market volatility suggesting that a more frequent disclosure of the earnings news is likely to lower uncertainty. Houston et al. (2010) find that a major reason for stopping guidance is a poor operating performance and find that stoppers’ information environment deteriorates after guidance cessation: analysts’ forecast error and dispersion increase. Chen et al. (2011) focus on guidance stoppers which publicly announced their decision and document a negative three-day returns around the announcement, a subsequent increase in analysts forecast dispersion and decreases in forecast accuracy.

Apart from the latter studies, most of the literature ignores the dynamic nature of earnings forecasts implicitly assuming that the voluntary disclosure choice regards a single-period decision, leading to a static interpretation of the phenomenon.

Recently the earnings forecast practice has become more regular and common practice, and its timing is increasingly bundled with earnings announcements (Berger, 2011; Rogers and Van Buskirk, 2013). Consistent with these tendency, managers avoid setting disclosure precedents that will be difficult to maintain and likely follow their existing disclosure practice, as they perceive significant costs to change guidance. Einhorn and Ziv (2008) suggest that such costs can result from investors' "learning" that managers are informed and developing an expectation for continued guidance. As a result managers acknowledge the importance of commitment to disclosure, sticking to a disclosure precedent once initiated. This new stream of research is consistent with managers giving priority to being coherent with their past forecasting history and adopting predetermined policies to guide their disclosure.

Characteristics of Managers Earnings Forecasts and Financial Analysts

Prior studies show that the release of earnings forecasts is an important tool to analysts and investors as they are engaged in strategic analysis in order to assess firm's value. The subsequent use and dissemination of information by these actors depends on managers' decision to disclose a particular information (Beyer et al., 2010). To this respect, previous studies examine the characteristics of management guidance and their consequences.

Bowen et al. (2005) provide evidence that market participants, such analysts, react not only to the content, but also to the timing and form of financial disclosures. Williams (1996) shows that earnings forecasts originating from firms with high prior forecast accuracy lead to greater earnings forecast revisions by analysts. Karamanou and Vafeas (2005) shows that more precise forecast reflect greater certainty, superior corporate governance and analyst following. Libby et al. (2006) experimentally show that forecast accuracy interacts with forecast form to determine analysts earnings revisions after earnings are reported. Lansford et al. (2013) find that firms providing disaggregated earnings guidance exhibit a more timely analysts forecasts revision and a larger reduction in analysts disagreement. Merkley et al. (2012), based on a relatively large hand-collected sample of earnings forecasts, find that disaggregation increases analysts' sensitivity to the news in managers' earnings guidance, suggesting that analysts find the guidance more credible.

In sum, previous research demonstrates that the choice of individual characteristics in a single-period setting do have an impact on the information environment. However whether the characteristics are sticky to a "pattern" over time and how this may influence analysts' behavior is still an open question. In particular: Does consistency in guidance characteristics have an impact, Do analysts recognize consistent qualitative disclosure across time and how do they react?

Building on these considerations, the predictions of this paper deal with the effects of consistency on the analysts' properties.

I expect the level-based measures of consistency to have a positive impact on the information environment, thus decreasing analysts dispersion and increasing analysts accuracy and analysts following. It seems reasonable to expect that the positive effect will perpetuate for the individual measures of consistency, however we need to consider that the nature of each attribute could have an effect beyond the influence of consistency. For this reason it is unclear to what extent a positive relation between consistency in individual characteristics and analysts' properties should be in place.

First, I test the analyst properties on consistency as a level-based measure and formalize the following hypotheses:

H1a: Analyst dispersion is negatively associated with the level-based measures of consistency (strong, semi-strong and weak)

H1b: Analyst accuracy is positively associated with the level-based measures of consistency (strong, semi-strong and weak)

H1c: Analyst following is positively associated with the level-based measures of consistency (strong, semi-strong and weak)

The second set of hypotheses deals with individual measures of consistency and their effect on the information environment. I state the hypotheses as follows:

H2a: Analyst dispersion is negatively associated with the characteristic-based measures of consistency (consistency in precision, disaggregation and additional qualitative information).

H2b: Analyst accuracy is positively associated with the characteristic-based measures of consistency (consistency in precision, disaggregation and additional qualitative information).

H2c: Analyst following is positively associated with the characteristic-based measures of consistency (consistency in precision, disaggregation and additional qualitative information).

2.3 DATA AND RESEARCH DESIGN

Sources

Data on management earnings forecasts are obtained from *Factiva* using the "*Press Release Newswire*" and "*Dow-Jones Business* News" sources for the North-America region. Financial analyst forecasts data are obtained from the Institutional Brokers Estimate System (*IBES)*. I use *Compustat* to collect financial data.

Sample selection

I hand collect management earnings forecasts from press releases issued for the years 2005-2013. I use Factiva to download candidate management earnings forecasts and follow Baginski et al. (2004) to perform the search. Using business newswires Dow Jones Business News ("DJBN") and Press Release Newswire ("PRN"), I look for the following set of keywords: *"expects earnings", "expects net", "expects income", "expects losses", "expects profits", and "expects results".* In addition, I look for three parallel lists where "*expects"* is replaced alternatively by *"forecasts", "predicts", and "sees".* This search yields 9,304 candidate earnings forecasts observations (7,752 for DJBN and 1,552 for PRN) downloaded in batches of 100 announcements per .txt file and corresponding to 2,505 firms' observations. I treat the press release earnings forecast as unit of observation.

Each company identifier (referred to as "CO" in Factiva) is then extracted from the downloaded text and, through a textual algorithm, matched to the common Compustat company name and ticker identifier. I manually verify these automated "candidate matches". Following Gong et al. (2011), I exclude guidance issued in prior years if already existing for the current year because these long-term forecasts contain more earnings uncertainty, and are not comparable to forecasts issued during the current period. This process yielded a total of 5,434 forecast observations, corresponding to 1,603 firm observations which include both quarterly and annual guidance. Press releases are content analyzed and forecast characteristics related information is manually reported in the classification scheme.

After a first screening of the reported headlines, 535 press releases are deleted as they do not refer to companies' future earnings but to "footnotes", "recap", "correction", "market talk" or appear to be generic. The sample is then divided into annual and quarterly forecasts, based on the forecasting period. For the purpose of this study only the annual subsample is considered, which yields a total of 2,263 observations corresponding to 946 firms. I require sample firms to exist in I/B/E/S database, leading to a final sample of 1,159 forecast observations.

Measures of consistency

For the purpose of this study predictions are tested on annual earnings forecasts consistently with Tang (2012), although this can limit the sample size, and involve two different types of consistency measures. As in the previous chapter, the first type captures the incremental level of consistency - thus providing insights into how many characteristics are unchanged from one period to the other -, while the second measure of consistency is based on the pattern of single characteristics as to distinguish among each other.

More precisely, three main characteristics are taken from previous literature[13] and defined as:F forecast precision, level of disaggregation and additional qualitative information.

For both settings, I classify firms as "consistent" based on persistence of characteristics (a set or a single one) from one fiscal year (*t-1*) to the next (*t*). This requires an earnings forecast to exist for at least two consecutive years. I assign a score at each firm-year based on the characteristics on which consistency applies and bind its definition to preceding fiscal year irrespective of a sequence of quarters. I assume that firms providing annual guidance with a certain set of characteristics at year *t-1* will be prone to provide guidance reflecting previous characteristics composition at year *t.*

In this case, I create three indicator variables corresponding to three possible levels of consistency (setting 1) and defined as follows:

- *Strong consistency*: refers to a dummy variable equal to 1 when all the three dimensions of interest - precision, disaggregation and additional information - in year *t* are identical to year *t-1*, 0 otherwise.
- *Semi-strong con*sistency: refers to a dummy variable equal to 1 when two[14] of the three dimensions of interest in year *t* are identical to year *t-1*, 0 otherwise.
- *Weak consistency*: refers to a dummy variable equal to 1 when only one[15] of the three dimensions of interest in year *t* is identical to year *t-1*, 0 otherwise.[16]

[13] For an extended review of the topic see Hirst et al. (2008).
[14] Notice that I strictly bind the definition of semi-strong consistency to the similarity of "two" dimensions instead of "at least two" in order to preserve mutually exclusive categories of consistency.
[15] Notice that, as for semi-strong, I strictly bind the definition of weak consistency to the similarity of "one" dimension instead of "at least one" in order to preserve mutually exclusive categories of consistency.
[16] See table 1 in Chapter 1 for some examples of consistency.

Next, I create three other indicator variables, one for each characteristic, in order to capture consistency at the characteristic-based level (setting 2). This represents a more specific measure and allows to draw inferences on the role and importance of each forecasts' attributes.

The consistency measures, in this case, are defined as follows[17]:

- *Consistency in precision*: refers to a dummy variable equal to 1 when the level of precision (i.e. point, range, open ended or qualitative) in year *t* is identical to year *t-1*, 0 otherwise.
- *Consistency in disaggregation*: refers to a dummy variable equal to 1 when the level of disaggregation (earnings only, revenues or sale, at least one major expense or detailed line items) in year *t* is identical to year *t-1*, 0 otherwise.
- *Consistency in additional qualitative information*: refers to an a dummy variable equal to 1 when the type of additional qualitative information (earnings explanation, CEO/CFO comment, update) in year *t* is identical to year *t-1*, 0 otherwise.

Empirical design

To test hypotheses 1 and 2 and see whether analysts' activity is sensitive to consistency, I consider three different analyst properties - dispersion, accuracy and analyst following - to be used as dependent variables.

I estimate three OLS models, one for each of the analyst properties, and regress them on the measures of consistency, plus a set of control variables. I use robust standard errors clustered by firm. All the continuous variables are winsorized at the first and 99th percentile. The main control variables in the models reflect: firm's performance, the magnitude of the earnings news, the probability that the firm meets or beats analysts' forecasts, the probability of losses, the earnings surprise, firm's growth, leverage, industry and size. Variable definitions are listed in the Appendix.

[17] See table 1 in Chapter 1 for some examples of consistency.

The models used are illustrated below:

Model 1

$$
\begin{aligned}
ANALYST\ (DISP,\ ACC,\ FOLLOW) = {} & \beta_0 + \beta_1\ CONS\_LEV_{it} + \beta_2\ ROA_{it} + \beta_3\ NEWS_{it} + \beta_4\ MEET_{it} + \\
& + \beta_5\ LOSS_{it} + \beta_6\ EARN\_DIFF_{\ it} + \beta_7\ GROWTH_{it} + \beta_8\ LEV_{it} + \\
& + \beta_9\ SIZE_{it} + \beta_{10}\ INDUSTRY_{it} + \varepsilon. \qquad (1)
\end{aligned}
$$

Model 2

$$
\begin{aligned}
ANALYST\ (DISP,\ ACC,\ FOLLOW) = {} & \beta_0 + \beta_1\ SINGLE\_CONS_{it} + \beta_2\ BREAK_{it} + \beta_3\ CHAR\_t0_{it} + \\
& + \beta_4\ ROA_{it} + \beta_5\ NEWS_{it} + \beta_6\ MEET_{\ it} + \beta_7\ LOSS_{it} + \\
& + \beta_8\ EARN\_DIFF_{it} + \beta_9\ GROWTH_{it} + \beta_{10}\ LEV_{it} + \beta_{11}\ SIZE_{it} + \\
& + \beta_{12}\ INDUSTRY_{it} + \varepsilon. \qquad (2)
\end{aligned}
$$

2.4 RESULTS

Descriptive Statistics

Table 1 presents information related to the distribution of the characteristics.

[INSERT TABLE 1 HERE]

Panel A shows that the vast majority of annual forecasts are issued with a range format (74.88%), 12.86% of the observations are qualitative forecasts and 10.31% are numerical point estimates, while only 1.95% are open-ended. Panel B shows that the management forecasts at minimum provide the earnings projection (lev. 0 disaggregation), more than half of the sample provide the revenue or sale item information (lev. 1 disaggregation), 18.29% accompany earnings with at least one major expense line item (lev. 2 disaggregation), while only 3.09% show more detailed line items (lev. 3 disaggregation). Panel C gives some information about the additional qualitative information. One quarter of the forecasts in the sample is bounded with CEO or CFO comments; almost 15% provide an explanation for the earnings estimate (of which 43.82% rely on internal attributions, while 37.08% on external attributions). Finally, 33.48% could be referred to as an earnings estimate update.

Table 2 reports data related to the distribution of the consistency measures.

[INSERT TABLE 2 HERE]

Panel A reveals that 11.12% of the observations are consistent at the strong level, 25.5% at the semi-strong level and 18.77% at the weak level. Panel B shows that, in terms of individual measures, 47.15% of the sample is consistent in precision, 35.54% is consistent in disaggregation and 20.46% is consistent in the type of additional information provided.

Table 3 illustrates the distribution of the sample and measures of consistency by industry.

[INSERT TABLE 3 HERE]

Panel A shows that the majority of observations belong to "other industry"[18] (16.87%), followed by retail (16.39%) and healthcare (15.19%). Panel B confirms the industry distribution for precision. The manufacturing, healthcare and retail industries are the most disaggregated at the revenues/sales level; the consumer non-durable and healthcare sectors display the most disaggregation at the major expenses level; the most disaggregated forecasts in terms of detailed line items level pertain to manufacturing firms. Panel C reports trends for the consistency measures. The semi-strong measure of consistency is prevalent for most of the sectors, except for the consumer durables which sees a prevalence of weak consistency. Among the individual measures, consistency in precision is generally the most prevalent followed by consistency in disaggregation.

Table 4 presents the distribution of the sample and measures by year.

[INSERT TABLE 4 HERE]

[18] I decide to keep financial institutions in the sample in order not to lose too many observations.

Panel A depicts a clear trend: most of the observations pertain to the first half of the sample years, which accounts for over 70% of the total number of observations. Indeed, there exist evidence supporting a decreasing trend in earnings forecast issued after 2008.[19] Panel B confirms the distribution of the characteristics by year. It shows a disproportioned amount of guidance bounded with CEO comments in 2005 and with update in 2006 and 2007. Panel C confirms the distribution of consistency measures by year with a prevalence of semi-strong consistency and consistency in precision over the years.

Table 5 summarizes the descriptive statistics for the set of regression variables.

[INSERT TABLE 5 HERE]

The distributions of the control variables are consistent with previous literature. On average, firms tend to be larger (followed by 11.38 financial analysts) and more profitable (incurring losses are only 5% of the sample). Almost 60% report bad news and disclose the earnings estimates on average 5 days before the earnings announcements. Managers spend on average 16% of their lives in the CEO position.

Table 6 reports Pearson correlations.

[INSERT TABLE 6 HERE]

The consistency measures based on levels are all negatively correlated as expected. The individual measures are positively correlated but correlations never exceed 0.52. The fact that the correlation is less than 0.52 means that each of the variables contain different information.

[19] Ciconte et al. (2013) document a decrease from 2008 to 2010 in their earnings forecast sample collected from the CIG database. A comparison with data obtained from the IBES-guidance database confirms that from 2009 earnings forecasts issuance drops to a 8% compared to the average 12% in the years 2004-2008. Also, the sample selection criteria and the source from which forecasts are extracted (*Factiva* press releases) contribute to justify such a distribution. Reasonably, when the data collection started, Factiva might not have been updated with the full press releases coverage, especially of recent years. In addition, drawing from alternative available sources of earnings forecasts, such as IBES Guidance, would have not allow the extensive collection of attributes given the different and limited nature of the data.

Empirical results for H1

As discussed earlier, H1a focuses on the effect of the level-based measures of consistency on analysts' dispersion. Therefore I use *dispersion* as the dependent variable. I run three different OLS regressions, one for each level of consistency (e.g. strong, semi-strong and weak). Table 7 reports tabulated results of the effect on analyst dispersion.

[INSERT TABLE 7 HERE]

Consistent with H1a, firms with a *strong* level of consistency experience lower analyst dispersion, the coefficient is negative and significant (p-value=0.008) which implies that a 1% increase in the probability of being strongly consistent would decreases dispersion by 2.6%, holding everything else equal. The more characteristics are stable over time, the less analysts' consensus is dispersed and uncertain. The coefficients on both *weak* and *semi-strong* are negative, but not significant. All the other control variables go in the expected directions and are significant, except for performance, loss and growth.

H1b focuses on the effect of the level of consistency on analysts' absolute error, which is a common used proxy for analysts' accuracy. I use *abs_err* as the dependent variable and three different models, each one assessing an incremental level of consistency. Table 8 reports tabulated results.

[INSERT TABLE 8 HERE]

The first regression shows a negative and significant coefficient (p-value=0.008) on *weak* consistency, meaning that when one of the three characteristics remains unchanged analysts are able to better predict firm's earnings. The result indicates that a 1% increase in the probability of being weakly consistent would result in an average decrease of analysts absolute error of 11%. In the second and third regressions the coefficients on *semi-strong* and *strong* consistency are not significant, suggesting that consistency in more than one characteristics do not have a real effect on analyst accuracy. Taken together, the results suggest that for analyst to be accurate what matters is the consistency of one characteristic among the three. All the other control variables go in the expected directions, although only news, meet, and leverage are statistically significant.

H1c predicts the effect of the level of consistency on analysts following. I use the average number of *analyst following* as the dependent variable. Table 9 reports tabulated results.

[INSERT TABLE 9 HERE]

All three models show that the coefficients on *weak*, *semi-strong* and *strong* are positively associated with analysts following, however only the *weak* measure of consistency is significant (p-value=0.009) suggesting once again that that the familiarity effect with characteristics from one period to the other works at the lowest level. Everything else being equal, this would result in analysts following increasing by 1.7%.

In sum, the results suggest that the commitment of managers to consistent disclosure have to some extent a positive impact on the information environment. Although earnings forecasts are voluntary disclosure and managers may still act opportunistically providing forecasts with a different level of detail, analysts benefit from managers being consistent with past choices. In fact, by reiterating a commitment to the characteristics of the forecasts, while managers cannot alter the news outcome, they can provide analysts with a familiar basis to interpret both favorable and unfavorable news.

While H1 captures the level of consistency from one period to the other and provides insights into how sensitive analysts' activity is to incremental consistency, the effects of individual characteristics consistency is still unknown.

Empirical results for H2

The second set of hypotheses tests the consistency of each characteristics on the properties of financial analysts in order to get more evidence on the role that they play individually. H2a focuses on the effect of individual consistency - in precision, in disaggregation and in additional information - on analysts' dispersion. I use *dispersion* as the dependent variable and run three different OLS models, one for each measure of consistency. In this case, the model is augmented with two variables in order to track the multi-period behavior of a single attribute, thus controlling for the specification of the characteristic at *time 0* and for its possible change after it has been consistent for at least one period (e.g. breaks). Table 10 shows tabulated results.

[INSERT TABLE 10 HERE]

In the three regressions the coefficients on single consistency specification are negative and significant (p-value=0.020; 0.025; 0.007), although consistency in precision has the largest impact. In fact, in terms of economic significance, a 1% increase in the probability of being consistent in precision corresponds to a decrease of 8.5% in analyst dispersion, while the probabilities of being consistent in disaggregation and additional information are associated with a decrease of respectively 7.2% and 4.5% in dispersion. The first and third regressions also report positive and significant coefficients on breaks (for precision p-value=0.033; for additional information p-value=0.028). The decrease of dispersion to which each characteristic contributes is most likely the result of a richer information environment as analysts become used to firm's projections with a certain degree of stability from period to period.

H2b predicts the effect of single consistency on analyst accuracy. I use *abs_err* as the dependent variable. Table 11 shows tabulated results.

[INSERT TABLE 11 HERE]

In the second regression, consistency in disaggregation is negatively associated with analysts absolute error and significant (p-value = 0.042), while break in disaggregation is positive and significant (p-value=0.008). To the extent that financial analysts rely on the line items provided with the earnings forecast and go through them, the result suggests that analysts accuracy may be favorably affected by firms providing exactly the same line items information[20].

H2c predicts the effects of single consistency on analyst following.

[INSERT TABLE 12 HERE]

The first regression in table 12 shows that the coefficient on consistency in precision is significantly positive (p-value=0.004). Consistently providing the same level of precision over time is indeed associated with an increase in analyst coverage. The coefficient on break in precision is significantly negative (p-value=0.002), supporting previous results. On the other hand, the coefficients of interest in both the second and third regressions are not statistically significant.

On the whole, the second set of results provide evidence that the decrease in analyst dispersion due to earnings forecasts' consistency is attributable to the consistency of the three characteristics – precision, disaggregation and additional information –, but with a predominant effect of the first one. Each of them contribute to some extent to enrich the information environment resulting in better and easily processible information. The improvement in analyst accuracy related to forecast consistency seems to be driven solely by consistency in the level of disaggregation, meaning that keeping the same level of detail in describing firm's future earnings estimates is crucial for analysts to align their expectations with firm's ones.

Earnings guidance is practiced by a large number of companies and is clearly welcomed by the analysts, even more when they do not vary over time, accommodating their activity of analysis. Analysts seem to be more willing to follow a new company whenever there exists some degree of consistency with the past regarding the precision with which earnings expectations are issued.

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[20] When the aggregated variable break is substituted by two variables, one for the positive and the other for the negative breaks, the significant effect transfers on the negative break, which remains positively associated to analysts absolute error.

2.5 ADDITIONAL ANALYSIS

The voluntary disclosure literature is based on the assumption that managers possess private information, which is strategically communicated to investors and analysts through earnings forecasts. However, from an empirical perspective the nature of the information communicated by managers is not always well understood. Bonsall et al. (2013) decompose earnings forecasts into macroeconomic and firm-specific factors and determine the extent to which voluntary disclosure provided by management include macroeconomic information content. Hutton et al. (2012) show that analyst forecasts are more accurate when a firm's prospects are linked to macroeconomic factor realizations. These studies discuss management's ability to process and incorporate timely macroeconomic information. Neverthless, management earnings forecasts may still convey macroeconomic information even when managers do not fully process and include them.

The latest global economic crisis that shocked the markets between late 2007 and 2009 constitutes a natural macroeconomic event that could have affect management private information as well as management earnings guidance per se'.

Due to the time coverage of the sample period, I run additional analysis to rule out the possibility that the results obtained are driven by the impact of economic crisis. To address this concern, I exclude the 2008 from the sample of analysis and rerun the regressions for two separate subsamples, respectively: 2005-2007 and 2009-2013. I expected both sign and significance of the coefficient to be aligned with previous results, unless the crisis have played a direct role in affecting forecasts characterization.

Consistent with the main tests, untabulated results show that the effects of consistency remain generally unchanged for the sub-sample 2005-2007. In other words, I can reasonably exclude that such a macroeconomic component has driven guidance pattern of characteristics and their effects on the information environment.

2.6 CONCLUSIVE REMARKS

Prior studies suggest different rationale behind managers' decision to issue earnings forecasts as well as to change or stop them, but in general they lack a multi-period approach. The very few adopting a dynamic approach do not provide evidence about the pattern of "inner" characteristics of management earnings forecast and their consequences on the information environment. Indeed, managers not only decide the timing and the informative content of disclosure but also its characteristics.

Bridging together these researches, the paper aims at empirically testing the effect of consistency on the properties of financial analysts' estimates: dispersion, accuracy and following.

Building on previous literature on guidance characteristics, I focus on a new definition of consistency based on: precision, level of disaggregation and additional qualitative information. I classify firm as "consistent" if a set of characteristics or the single characteristic persist over time remaining unchanged.

Preliminary results reveal that consistency in forecasts characteristics contributes to enrich a firm's information environment and help analysts to align their expectations with managers. More precisely, when the whole set of characteristics is stable from one year to the next (i.e. strong consistency) analyst dispersion decreases. Also, when one of the three characteristics is consistent both analysts accuracy and following increase. When looking at individual measures of consistency, the positive effect on analyst dispersion seems to be driven by the three characteristics but with a larger impact of consistency in precision. Accuracy is then improved by the consistency in the level of disaggregation, while the increase in analyst coverage is attributable to the level of precision being unchanged from year to year.

The paper contributes to the current debate on guidance practice. It suggests that beyond the measure of guidance frequency, the study of the inner characteristics of earnings forecasts in a multi-period perspective especially deserves attention, given that managers have greater discretion over their choice and analysts' behavior may be influenced by them. The study also add to the recent literature on firms that stop providing earnings guidance demonstrating that changes in guidance pattern may not necessarily relates to the interruption of guidance itself, but could be analyzed at a finer level. The evidence should be of interest to academics who study corporate voluntary disclosure, as well as to practitioners and managers who are responsible of firms' disclosure policies.

APPENDIX

Variable Definitions

Consistency measures

WEAK *= indicator variable equal to 1 if one of the three dimensions of interest in year t is identical to that in year t-1, 0 otherwise.*

SEMI-STRONG *= indicator variable equal to 1 if two of the three dimensions of interest in year t are identical to that in year t-1, 0 otherwise.*

STRONG *= indicator variable equal to 1 if the three dimensions of interest in year t are identical to that in year t-1, 0 otherwise.*

CONS_PREC *= indicator variable equal to 1 when the level of precision (i.e. point, range, open ended or qualitative) in year t is identical to year t-1, 0 otherwise.*

CONS_DISAG *= indicator variable equal to 1 when the level of disaggregation (earnings only, revenues or sale, at least one major expense or detailed line items) in year t is identical to year t-1, 0 otherwise.*

CONS_ADD *= indicator variable equal to 1 when the type of additional qualitative information (earnings explanation, CEO/CFO comment, update) in year t is identical to year t-1, 0 otherwise.*

BREAK_PREC *= indicator variable equal to 1 when the forecast has been classified as consistent with respect to the previous period (t-1) but displays a different level of precision (point, range, open-end, qualitative) in the subsequent period (t+1), 0 otherwise.*

BREAK_DISAG *= indicator variable equal to 1 when the forecast has been classified as consistent with respect to the previous period (t-1) but displays a different level of disaggregation (earnings only, revenues or sale, at least one major expense, other) in the subsequent period, 0 otherwise.*

BREAK_ADD *= indicator variable equal to 1 when the forecast has been classified as consistent with respect to the previous period (t-1) but displays a different level of additional information (earnings explanation, CEO/CFO comment, update) in the subsequent period (t+1), 0 otherwise.*

Analyst Properties

DISPERSION *= standard deviation of analysts' EPS forecasts for year t in the most recent consensus from the IBES summary data*

ACCURACY *= absolute difference between realized earnings and the most recent analysts' consensus estimates compiled before the earnings announcement*

FOLLOW *= average number of analysts following a company in year t*

Guidance motivation variables

NEWS *= absolute difference between the company's earnings estimates (the midpoint is used for range estimates) and the most recent analyst consensus from the IBES summary data before the disclosure event, scaled by the absolute realization*

MEET *= indicator variable equal to 1 if realized annual EPS is greater than or equal to analysts' consensus forecasts in year t, 0 otherwise.*

Firm Performance

ROA *= return on assets in year t-1*

LOSS *= indicator variable equal to 1 if the firm suffered a loss in year t-1*

<u>Other Control variables</u>

EARN_DIFF *= difference between realized EPS in year t-1 and realized EPS in year t scaled by realized EPS in year t.*

GROWTH*=difference between sales in year t and sales in year t-1 scaled by sales in year t-1*

LEV *= ratio of total debt over total assets at the end of year t-1*

SIZE *= natural log of total sales in year t*

INDUSTRY *= industry classification based on the 10 Fama-French.*

Table 1. Distribution of the Characteristics: precision, disaggregation and additional information

Panel A

By precision	**Frequency**	**Percent**
Point	190	10.31
Range	1,380	74.88
Open End	36	1.95
Qualitative	237	12.86
Total	1,843	100

Panel B

By disaggregation	**Frequency**	**Percent**
Level 0	1,843	100
Level 1	1,004	54.48
Level 2	337	18.29
Level 3	57	3.09
Total	1,843	-

Panel C

By additional information	**Frequency**	**Percent**
Earnings Explanation	267	14.49
Internal Attribution	*117*	*43.82*
External Attribution	*99*	*37.08*
Both	*47*	*17.6*
CEO/CFO comment	475	25.77
Update	617	33.48
Total	1,843	-

Table 2. Distribution of the consistency measures. Level-based and individual

Panel A

By consistency (level)	Frequency	Percent
Strong	205	11.12
Semi-strong	470	25.5
Weak	346	18.77
No consistency	822	44.6
Total	1,843	100

Panel B

By consistency (individual)	Frequency	Percent
Precision	869	47.15
Disaggregation	655	35.54
Additional info	377	20.46
Precision, disaggregation, additional info	205	11.12

Table 3. Distribution of observations, characteristics and measures of consistency by industry

Panel A

By industry	**Frequency (Obs.)**	**Percent**
Consumer Non-Durables	224	12.15
Consumer Durables	73	3.96
Manufacturing	267	14.49
Energy	45	2.44
Hi-Tech	207	11.23
Telecom	25	1.36
Shops/Retail	302	16.39
Healthcare	280	15.19
Utilities	109	5.91
Other (finance included)	311	16.87
Total	1,843	100

Panel B

	Precision				Disaggregation				Additional Qualitative Information				
Industry	**Point**	**Range**	**Open**	**Qual.**	**Lev 0**	**Lev 1**	**Lev 2**	**Lev 3**	**Eps explanation**	**Internal**	**External**	**CEO comm.**	**Update**
Consumer Non-Durables	15	169	15	18	224	109	73	7	32	22	15	67	86
Consumer Durables	2	58	0	10	73	41	26	1	13	8	6	24	28
Manufacturing	34	214	2	24	267	179	43	12	45	27	26	79	91
Energy	3	22	1	20	45	18	21	8	14	3	13	9	13
Hi-Tech	26	154	3	28	207	144	19	5	24	18	14	53	58
Telecom	5	17	2	6	25	15	5	1	4	1	3	4	5
Shops/Retail	26	240	1	36	302	148	29	6	28	14	16	66	114
Healthcare	19	218	2	31	280	174	66	7	34	20	20	57	90
Utilities	8	98	0	4	109	6	15	4	15	9	7	22	31
Other (finance included)	48	195	12	57	311	126	32	4	49	36	22	78	83
Total	**186**	**1,385**	**38**	**234**	**1,843**	**960**	**329**	**55**	**258**	**158**	**142**	**459**	**485**

Panel C

Industry	Strong cons.	Semi-strong cons.	Weak cons.	Cons. (Precision)	Cons. (Disaggreg.)	Cons. (Add. Info)	Break (precision)	Break (disaggreg.)	Break (Add. Info)
Consumer Non-Durables	33	65	65	139	99	58	39	25	30
Consumer Durables	7	17	26	44	22	12	13	7	7
Manufacturing	27	80	59	135	106	48	45	28	25
Energy	3	10	10	22	11	6	5	4	1
Hi-Tech	16	37	25	63	54	30	28	9	10
Telecom	2	5	3	5	7	4	3	0	3
Shops/Retail	36	85	45	152	108	71	52	25	27
Healthcare	36	74	54	149	98	74	42	22	23
Utilities	17	32	14	51	48	21	27	2	5
Other (finance included)	28	65	45	109	102	53	56	19	14
Total	**205**	**470**	**346**	**869**	**655**	**377**	**310**	**141**	**145**

Table 4. Distribution of observations, characteristics and measures of consistency by year

Panel A

By year	Frequency	Percent
2004	29	1.57
2005	365	19.8
2006	424	23.01
2007	293	15.9
2008	230	12.48
2009	139	7.54
2010	124	6.73
2011	114	6.19
2012	119	6.46
2013	6	0.33
Total	1,843	100

Panel B

	Precision				Disaggregation				Additional Qualitative Information				
Year	**Point**	**Range**	**Open**	**Qual.**	**Lev 0**	**Lev 1**	**Lev 2**	**Lev 3**	**Eps explanation**	**Internal**	**External**	**CEO comm.**	**Update**
2004	5	10	0	14	29	14	1	0	5	6	2	7	14
2005	43	270	2	50	365	179	44	6	55	40	30	153	57
2006	47	326	6	45	424	208	50	4	61	40	32	90	133
2007	23	232	3	35	293	172	55	7	31	22	11	39	124
2008	23	171	12	24	230	147	47	7	20	10	12	30	93
2009	11	106	3	19	139	70	43	6	34	15	22	47	61
2010	12	85	6	21	124	76	32	11	21	9	12	37	34
2011	9	91	2	12	114	75	32	7	21	13	11	29	50
2012	17	84	2	16	119	61	31	9	18	8	14	40	50
2013	0	5	0	1	6	2	2	0	1	1	0	3	1
Total	**190**	**1380**	**36**	**237**	**1843**	**1004**	**337**	**57**	**267**	**164**	**146**	**475**	**617**

Panel C

Year	**Strong cons.**	**Semi-strong cons.**	**Weak cons.**	**Cons. (Precision)**	**Cons. (Disaggreg.)**	**Cons. (Add. Info)**	**Break (precision)**	**Break (disaggreg.)**	**Break (Add. Info)**
2004	6	4	3	13	9	7	0	3	4
2005	28	56	37	106	82	45	26	23	23
2006	34	113	68	187	138	71	66	25	28
2007	53	74	56	150	128	85	57	30	38
2008	33	64	39	115	90	61	52	17	22
2009	9	42	41	77	49	26	24	13	12
2010	17	37	31	72	55	29	26	16	12
2011	14	38	30	70	51	27	33	10	6
2012	9	39	40	74	48	23	43	4	2
2013	2	3	1	5	5	3	4	0	0
Total	**205**	**470**	**346**	**869**	**655**	**377**	**331**	**141**	**147**

Table 5: Descriptive Statistics

				N. 1159			
Variable	Mean	SD	Min	0.25	Median	0.75	Max
EARN_DIFF	-74.16	159.6	-454	-102	-15.43	9.34	100.84
ROA	0.05	0.11	-0.54	0.03	0.06	0.1	0.3
NEWS	0.19	0.61	-0.62	-0.15	0.00	0.47	1.49
MEET	0.75	0.43	0.00	0.00	1.00	1.00	1.00
LOSS	0.05	0.22	0.00	0.00	0.00	0.00	1.00
GROWTH	0.31	1.03	-0.81	-0.01	0.00	0.20	2.95
SIZE	7.76	1.88	-2.42	6.53	7.90	9.09	13.01
LEV	0.18	0.16	0.00	0.04	0.15	0.28	0.72
INDUSTRY	5.96	3.03	1.00	3.00	7.00	8.00	10.00
DISP	0.05	0.08	0.00	0.01	0.02	0.05	0.57
ABS_ERR	0.03	0.17	-0.78	-0.00	0.02	0.06	0.69
FOLLOW	11.38	7.05	1.00	5.00	10.00	16.00	30.00

Table 6. Pearson Correlations between the variables

Panel A

Variable Name		1)	2)	3)	4)	5)	6)	7)	8)	9)
1)	strong	1								
2)	semi strong	-0.2070*	1							
3)	weak	-0.1701*	-0.2813*	1						
4)	cons_prec	0.3745*	0.5222*	0.1944*	1					
5)	cons_disagg	0.4764*	0.5357*	-0.1334*	0.5227*	1				
6)	cons_add	0.6976*	0.1230*	-0.1198*	0.3348*	0.3092*	1			
7)	break_prec	0.2211*	0.2516*	0.0755*	0.4953*	0.2669*	0.2043*	1		
8)	break_disagg	0.2617*	0.1407*	-0.0391	0.2107*	0.3876*	0.1577*	-0.0017	1	
9)	break_add	0.4755*	0.0345	-0.0851*	0.2154*	0.2166*	0.5806*	-0.0021	0.2393*	1

Panel B

Variable Name		1)	2)	3)	4)	5)	6)	7)	8)	9)	10)	11)	12)	13)	14)	15)	16)	17)	18)	19)	20)	21)	22)	23)
1)	prec_t0	1																						
2)	disag_t0	0.0373	1																					
3)	add_t0	-0.0724*	0.0139	1																				
4)	strong	-0.019	0.0427	0.0855*	1																			
5)	semi-strong	-0.0505*	-0.0044	-0.0106	-0.2070*	1																		
6)	weak	-0.0019	-0.0345	-0.1390*	-0.1701*	-0.2813*	1																	
7)	cons_prec	-0.0975*	0.0101	-0.0561*	0.3745*	0.5222*	0.1944*	1																
8)	cons_disag	-0.0258	0.0117	-0.0365	0.4764*	0.5357*	-0.1334*	0.5227*	1															
9)	cons_add	-0.0042	0.0306	0.1551*	0.6976*	0.1230*	-0.1198*	0.3348*	0.3092*	1														
10)	break_prec	-0.1134*	0.0148	0.0302	0.2211*	0.2516*	0.0755*	0.4953*	0.2669*	0.2043*	1													
11)	break_disag	-0.017	-0.0145	-0.0342	0.2617*	0.1407*	-0.0391	0.2107*	0.3876*	0.1577*	-0.0017	1												
12)	break_add	-0.0065	0.022	0.0550*	0.4755*	0.0345	-0.0851*	0.2154*	0.2166*	0.5806*	-0.0021	0.2393*	1											
13)	news	0.0891*	0.0630*	0.0024	0.0507*	-0.0124	-0.0325	0.0118	0.0098	0.035	0.0051	-0.0249	-0.0032	1										
14)	meet	-0.0988*	-0.0507	-0.0031	-0.036	0.0255	0.0107	-0.0123	0.0007	-0.0058	-0.006	0.0043	0.01	-0.0910*	1									
15)	loss	0.1527*	0.035	-0.0224	-0.0108	-0.0694*	0.0028	-0.0617*	-0.0752*	-0.0074	-0.0098	-0.0405	-0.0422	0.2082*	-0.1722*	1								
16)	earn_diff	-0.0264	-0.1091*	0.0562*	0.0083	-0.026	-0.0683*	-0.0438	-0.0285	-0.0152	0.0066	-0.0528*	-0.0206	0.1498*	-0.0963*	0.1233*	1							
17)	sale_gr	-0.0007	0.0157	0.0233	-0.041	-0.0791*	-0.0974*	-0.1511*	-0.1012*	-0.0565*	-0.0555*	-0.0414	-0.0226	-0.0084	0.0723*	-0.0851*	-0.1353*	1						
18)	lever	0.0483*	0.0367	-0.0048	0.0217	-0.0007	-0.0148	0.0224	0.007	-0.0012	0.0295	-0.019	0.0148	0.0017	-0.0298	-0.0087	0.041	0.0586*	1					
19)	FFind10	0.0214	0.0492*	0.0750*	-0.0027	-0.0345	-0.1215*	-0.1182*	-0.0336	-0.0126	0.0169	-0.0666*	-0.0778*	-0.0418	-0.003	0.0377	0.0161	0.0636*	-0.0225	1				
20)	lsale	-0.0587*	0.1582*	-0.1259*	0.0329	0.1140*	0.1176*	0.1925*	0.1257*	0.0508*	0.0616*	0.0878*	0.0674*	-0.0848*	0.1248*	-0.3372*	-0.4280*	0.2373*	0.1327*	-0.0049	1			
21)	Dispersion	0.2015*	0.0550*	-0.1239*	-0.0167	-0.0057	0.0056	-0.0107	-0.0155	-0.0142	0.0168	0.0261	0.0064	0.1120*	-0.0863*	0.2032*	0.004	0.0159	0.1218*	0.0815*	0.0798*	1		
22)	Abs_err	0.0186	-0.0018	-0.0126	-0.0209	0.0479	-0.0219	0.0164	0.0073	0.0056	-0.0006	0.0326	0.0131	-0.2267*	0.4705*	-0.0539*	-0.0499*	-0.0044	0.0788*	0.0063	0.0505*	0.0478	1	
23)	Following	-0.0109	0.0578*	-0.1090*	-0.0155	0.0851*	0.1335*	0.1124*	0.0831*	0.0404	0.0354	0.0714*	0.0215	-0.0797*	0.1394*	-0.1718*	-0.3736*	0.1544*	-0.0971*	0.0646*	0.5898*	-0.0713*	0.0299	1

Table 7. Effect of level-based consistency on Analysts Dispersion (Eq. 1)

Dependent Variable: Analysts Dispersion			
	H1a Weak Consistency	***H1a Semi-strong Consistency***	***H1a Strong Consistency***
WEAK	-0.000		
	(0.00)		
SEMI-STRONG		-0.001	
		(0.00)	
STRONG			-0.012***
			(0.00)
ROA	-0.032	-0.032	-0.028
	(0.02)	(0.02)	(0.02)
NEWS	0.010*	0.010*	0.011*
	(0.00)	(0.00)	(0.00)
MEET	-0.012**	-0.012**	-0.013**
	(0.00)	(0.00)	(0.00)
LOSS	0.032	0.032	0.033
	(0.02)	(0.02)	(0.02)
EARN_DIFF	0.000***	0.000***	0.000***
	(0.00)	(0.00)	(0.00)
GROWTH	-0.002	-0.002	-0.002
	(0.00)	(0.00)	(0.00)
LEV	0.044**	0.044**	0.045***
	(0.01)	(0.01)	(0.01)
INDUSTRY	0.002**	0.002**	0.002**
	(0.00)	(0.00)	(0.00)
SIZE	0.006***	0.006***	0.006***
	(0.00)	(0.00)	(0.00)
INTERCEPT	-0.017	-0.017	-0.016
	(0.01)	(0.01)	(0.01)
R-squared	0.085	0.085	0.088
No. of Obs.	1,159	1,159	1,159
Model F-Test	6.33	6.32	6.35
	(0.0000)	(0.0000)	(0.0000)

All continuous variables are winsorized at the first and 99th percentiles to alleviate the effects of outliers on the analysis. Robust standard errors clustered by firm and year are reported. * Statistical significance at the 0.10 level, using a two-tailed test. ** Statistical significance at the 0.05 level, using a two-tailed test. *** Statistical significance at the 0.01 level.

Table 8. Effect of level-based consistency on Analysts Accuracy (Eq. 1)

Dependent Variable: Analysts Absolut Error			
	H1b Weak Consistency	***H1b Semi-strong Consistency***	***H1b Strong Consistency***
WEAK	-0.018**		
	(0.01)		
SEMISTRONG		0.007	
		(0.01)	
STRONG			-0.002
			(0.01)
ROA	0.131	0.131	0.133
	(0.09)	(0.09)	(0.09)
NEWS	-0.041***	-0.041***	-0.041***
	(0.01)	(0.01)	(0.01)
MEET	0.151***	0.151***	0.151***
	(0.01)	(0.01)	(0.01)
LOSS	0.066	0.066	0.065
	(0.04)	(0.04)	(0.04)
EARN_DIFF	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)
GROWTH	-0.006	-0.005	-0.005
	(0.00)	(0.00)	(0.00)
LEV	0.0102**	0.0104***	0.0104***
	(0.03)	(0.03)	(0.03)
INDUSTRY	0.001	0.001	0.001
	(0.00)	(0.00)	(0.00)
SIZE	0.001	0.000	0.001
	(0.00)	(0.00)	(0.00)
INTERCEPT	-0.126***	-0.126***	-0.125***
	(0.03)	(0.03)	(0.03)
R-squared	0.273	0.271	0.271
No. of Obs.	1,159	1,159	1,159
Model F-Test	23.27	22.78	22.94
	(0.0000)	(0.0000)	(0.0000)

All continuous variables are winsorized at the first and 99th percentiles to alleviate the effects of outliers on the analysis. Robust standard errors clustered by firm and year are reported. * Statistical significance at the 0.10 level, using a two-tailed test. ** Statistical significance at the 0.05 level, using a two-tailed test. *** Statistical significance at the 0.01 level.

Table 9. Effects of level-based consistency on Analysts Following (Eq. 1)

Dependent Variable: Analysts Following			
	H1c Weak Consistency	***H1c Semi-strong Consistency***	***H1c Strong Consistency***
WEAK	1.000**		
	(0.38)		
SEMISTRONG		0.197	
		(0.32)	
STRONG			0.125
			(0.45)
ROA	17.065***	16.741***	16.813***
	(2.67)	(2.72)	(2.71)
NEWS	0.346	0.302	0.309
	(0.25)	(0.25)	(0.25)
MEET	0.714*	0.719*	0.719*
	(0.34)	(0.34)	(0.34)
LOSS	3.577***	3.613***	3.612***
	(0.88)	(0.89)	(0.89)
EARN_DIFF	-0.003**	-0.003**	-0.003**
	(0.00)	(0.00)	(0.00)
GROWTH	0.063	0.027	0.016
	(0.16)	(0.16)	(0.15)
LEV	-7.922***	-8.041***	-8.040***
	(1.00)	(1.01)	(1.01)
INDUSTRY	0.207***	0.198***	0.197***
	(0.04)	(0.04)	(0.04)
SIZE	2.180***	2.211***	2.219***
	(0.09)	(0.09)	(0.09)
INTERCEPT	-8.264***	-8.263	-8.260***
	(0.82)	(0.82)	(0.82)
R-squared	0.455	0.452	0.452
No. of Obs.	1,159	1,159	1,159
Model F-Test	102.91	102.54	102.16
	(0.0000)	(0.0000)	(0.0000)

All continuous variables are winsorized at the first and 99th percentiles to alleviate the effects of outliers on the analysis. Robust standard errors clustered by firm and year are reported. * Statistical significance at the 0.10 level, using a two-tailed test. ** Statistical significance at the 0.05 level, using a two-tailed test. *** Statistical significance at the 0.01 level.

Table 10. Effects of individual consistency on Analysts Dispersion (Eq. 2)

Dependent Variable: Analysts Dispersion			
	H2a Consistency in Precision	***H2a Consistency in Disaggreg.***	***H2a Consistency in Add. Info***
PREC_T0	-0.008		
	(0.01)		
CONS_PREC	-0.009*		
	(0.00)		
BREAK_PREC	0.012*		
	(0.01)		
DISAG_T0		0.004	
		(0.00)	
CONS_DISAG		-0.010*	
		(0.00)	
BREAK_DISAG		0.012	
		(0.01)	
ADD_T0			-0.001
			(0.00)
CONS_ADD			-0.011**
			(0.00)
BREAK_ADD			0.013*
			(0.01)
ROA	-0.031	-0.025	-0.029
	(0.02)	(0.02)	(0.03)
NEWS	0.011*	0.010*	0.010*
	(0.00)	(0.00)	(0.00)
MEET	-0.013**	-0.012**	-0.013**
	(0.00)	(0.00)	(0.00)
LOSS	0.029	0.032	0.032
	(0.02)	(0.02)	(0.02)
EARN_DIFF	0.000***	0.000***	0.000***
	(0.00)	(0.00)	(0.00)
GROWTH	-0.003	-0.002	-0.002
	(0.00)	(0.00)	(0.00)
LEV	0.045**	0.044**	0.045**
	(0.01)	(0.01)	(0.01)
INDUSTRY	0.002**	0.002**	0.002**
	(0.00)	(0.00)	(0.00)
SIZE	0.007***	0.006***	0.006***
	(0.00)	(0.00)	(0.00)
INTERCEPT	-0.002	-0.025*	-0.005
	(0.02)	(0.01)	(0.01)
R-squared	0.093	0.093	0.091
No. of Obs.	1,159	1,159	1,159
Model F-Test	6.04	5.90	5.55
	(0.0000)	(0.0000)	(0.0000)

All continuous variables are winsorized at the first and 99th percentiles to alleviate the effects of outliers on the analysis. Robust standard errors clustered by firm and year are reported. * Statistical significance at the 0.10 level, using a two-tailed test. ** Statistical significance at the 0.05 level, using a two-tailed test. *** Statistical significance at the 0.01 level.

Table 11. Effects of individual consistency on Analysts Accuracy (Eq. 2)

Dependent Variable: Analysts Absolute Error			
	H2b Consistency in Precision	***H2b Consistency in Disaggreg.***	***H2b Consistency in Add. Info***
PREC_T0	-0.003		
	(0.01)		
CONS_PREC	0.000		
	(0.01)		
BREAK_PREC	-0.000		
	(0.01)		
DISAG_T0		0.004	
		(0.00)	
CONS_DISAG		-0.016*	
		(0.01)	
BREAK_DISAG		0.038**	
		(0.01)	
ADD_T0			-0.000
			(0.00)
CONS_ADD			0.000
			(0.01)
BREAK_ADD			0.012
			(0.02)
ROA	0.132	0.145	0.129
	(0.09)	(0.09)	(0.09)
NEWS	-0.041***	-0.041***	-0.041***
	(0.01)	(0.01)	(0.01)
MEET	0.151***	0.0152***	0.151***
	(0.01)	(0.01)	(0.01)
LOSS	0.065	0.067	0.065
	(0.04)	(0.04)	(0.04)
EARN_DIFF	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)
GROWTH	-0.005	-0.005	-0.005
	(0.00)	(0.00)	(0.00)
LEV	0.105**	0.105***	0.104***
	(0.03)	(0.03)	(0.03)
INDUSTRY	0.001	0.001	0.001
	(0.00)	(0.00)	(0.00)
SIZE	0.001	0.000	0.000
	(0.00)	(0.00)	(0.00)
INTERCEPT	-0.121***	-0.136***	-0.124***
	(0.03)	(0.03)	(0.03)
R-squared	0.271	0.277	0.271
No. of Obs.	1,159	1,159	1,159
Model F-Test	19.00	19.27	19.12
	(0.0000)	(0.0000)	(0.0000)

All continuous variables are winsorized at the first and 99th percentiles to alleviate the effects of outliers on the analysis. Robust standard errors clustered by firm and year are reported. * Statistical significance at the 0.10 level, using a two-tailed test. ** Statistical significance at the 0.05 level, using a two-tailed test. *** Statistical significance at the 0.01 level.

Table 12. Effects of individual consistency on Analysts Following (Eq. 2)

Dependent Variable: Analysts Following			
	H2c Consistency in Precision	***H2c Consistency in Disaggreg.***	***H2c Consistency in Add. Info***
PREC_T0	-0.832		
	(0.47)		
CONS_PREC	1.006**		
	(0.35)		
BREAK_PREC	-1.290**		
	(0.41)		
DISAG_T0		-0.208	
		(0.14)	
CONS_DISAG		-0.083	
		(0.32)	
BREAK_DISAG		0.695	
		(0.59)	-0.101
ADD_T0			(0.08)
			0.697
CONS_ADD			(0.52)
			-0.614
BREAK_ADD			(0.65)
ROA	16.622***	16.880***	16.715***
	(2.68)	(2.74)	2.73)
NEWS	0.284	0.355	0.286
	(0.25)	(0.25)	(0.25)
MEET	0.703*	0.693*	0.725*
	(0.34)	(0.34)	(0.34)
LOSS	3.730***	3.664***	3.484***
	(0.89)	(0.89)	(0.89)
EARN_DIFF	-0.003**	-0.003**	-0.003**
	(0.00)	(0.00)	(0.00)
GROWTH	0.081	0.022	0.038
	(0.16)	(0.16)	(0.15)
LEVERAGE	-7.800***	-7.956***	-7.977***
	(1.02)	(1.01)	(1.02)
INDUSTRY	0.213***	0.201***	0.197***
	(0.04)	(0.04)	(0.04)
SIZE	2.162***	2.233***	2.189***
	(0.09)	(0.09)	(0.09)
INTERCEPT	-6.673***	-7.720***	-7.479***
	(1.20)	(0.86)	(1.06)
R-squared	0.458	0.454	0.453
No. of Obs.	1,159	1,159	1,159
Model F-Test	88.61	85.37	85.91
	(0.0000)	(0.0000)	(0.0000)

All continuous variables are winsorized at the first and 99th percentiles to alleviate the effects of outliers on the analysis. Robust standard errors clustered by firm and year are reported. * Statistical significance at the 0.10 level, using a two-tailed test. ** Statistical significance at the 0.05 level, using a two-tailed test. *** Statistical significance at the 0.01 level.

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CHAPTER 3

Management Earnings Forecasts, Impression Management and the Probability of Missing the Earnings Target

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Management Earnings Forecasts, Impression Management and the Probability of Missing the Earnings Target

ABSTRACT

This paper investigates whether the qualitative features of management earnings forecasts have predictive power in explaining firms' missing the earnings target. More precisely, I examine whether the consistency in guidance characteristics and the tone accompanying the earnings projections significantly predict the probability that a firm misses the earnings expectations in the subsequent period. The results suggest that consistency in precision and disaggregation positively influence the probability of missing the target in the subsequent fiscal year, while the impression management score is negatively related to it. When examining the different specifications of consistency, I find that earnings projections consistently given in the form of qualitative description, disaggregated at the expenses level and accompanied by explanations are positively associated with the probability of missing the earnings target in the subsequent period. This paper represents an incremental contribution to the collective understanding of the phenomenon of firms' missing the earnings target, while adding to the understanding of guidance characteristics and their role as part of a wider disclosure strategy. Also, the paper extends the impression management literature by providing evidence of a link between managers' use of tone in press releases and future earnings expectations.

Keywords: Management Earnings Forecasts, Consistency, Impression Management, Tone, Missing Earnings Expectations

Data Availability: Data used in this study are available from public sources indicated in the text.

3.1 INTRODUCTION

This paper examines whether the qualitative features of management earnings forecasts have predictive power in explaining firms' missing the earnings target. More precisely, I explore whether the consistency in guidance characteristics and the tone accompanying the earnings projections significantly predict the probability that a firm misses analyst forecasts in the subsequent period.

Considerable research explores the "meet or beat" phenomenon and the importance assigned to meeting earnings expectations is not surprising given the relevance of earnings information. Over the past decade, numerous studies suggest that meeting or beating analysts' expectations has become increasingly common (Matsumoto 2002; Brown and Caylor 2005). Prior studies also present evidence that the market assigns a premium to meeting or beating analyst expectations even after controlling for the news in earnings (Bartov et al. 2002; Kasznik and McNichols 2002) and that there is a market penalty to missing expectations for high-growth firms (Skinner and Sloan 2002). It seems intuitive though that managers would seek to increase earnings (e.g. bonuses, stock price, and labor-market reputation, among other incentives, increase with earnings).

However, less intuitive is why managers miss the earnings targets and which factors could explain such a phenomenon. While many prior studies document that firms strive to meet or beat earnings targets (Burgstahler and Dichev 1997; Cheng and Warfield 2005), or examines specific incentives that induce managers to depress earnings to miss important earnings targets (McAnally et al. 2008), I am aware of no study that considers the phenomenon and try to link it to qualitative features of corporate voluntary disclosure.

Existent research on management earnings forecasts largely focuses on assessing the information content of firms' quantitative disclosure, based on earnings metrics or other quantitative line items projections. However, a significant amount of disclosure is qualitative in nature and research provides substantially less attention to the issue.

Further, research analyzing earnings guidance put a great deal of emphasis on antecedents and consequences leaving the examination of forecast characteristics and the role they play as part of a dynamic disclosure strategy as an open issue. For example, existing research on earnings guidance largely focus on why managers issue a forecast and the likely consequences of this decision (Ajinkya and Gift 1984; Skinner 1994; Stocken 2000; Verrecchia 2001).

Using a sample of 1,104 firm-years observations for US companies, this paper examines whether: i) the consistency in management earnings forecasts characteristics ii) the set of specifications of a single characteristic conditional on consistency, and iii) the tone accompanying the management earnings forecasts, have predictive power with respect to a firms' probability of missing the earnings expectation in the subsequent period.

I start the analysis by exploring whether or not a firm misses analyst forecasts in the subsequent fiscal year. I construct the measures of consistency for both the selected characteristics - precision, level of disaggregation and additional qualitative information -, and for the related specifications (i.e. point, range, level 1 disaggregation, level 2 disaggregation, CEO comment, etc…). I then collect the number of positive and negative words for each company's earnings forecast using a specific wordlist for financial and accounting investigation purposes (Henry, 2006) in order to build the impression management score.

Using a logistic regression design, I first focus on the role of consistency in single characteristics and tone separately. I then augment the regression model in order to observe the joint actions of the two. I find that consistency in precision and disaggregation positively influence the probability of missing the target in the subsequent year, while the impression management score is negatively related to the probability of missing the target. The results hold for the augmented model as well.

Next, I focus on the role of each characteristics specification (conditional on consistency) and tone. I run a separate regression for the consistency measures and progressively include the impression management score and a variable for the total word count in each document. I find that the intercept, which capture the residual specification of precision (i.e. the earnings estimate is consistently given in the form of qualitative description at time *t*), is positively associated with the probability of missing the earnings target at time *t+1*. When *TONE* is added to the model, it remains negatively related to the probability of missing, while the word count is positive. Further, the residual specification of disaggregation (i.e. the earnings estimate is consistently disaggregated at the expenses level at time *t*) and the residual specification of additional information (i.e. the earnings estimate is consistently accompanied by explanations at time *t*) are positively associated with the probability of missing the earnings target at time *t+1*.

This study offers several contributions to the literature. First it represents an incremental contribution to the collective understanding of the phenomenon of firms' missing the earnings target. Considerable research explores the "meet or beat" phenomenon because it is intuitive that managers would seek to increase earnings (e.g., bonuses, stock price, and labor-market reputation, among other incentives, increase with earnings). Less intuitive is predicting whenever a firm is not able to meet the earnings expectation (or choose not to do so). This is the first study to examine whether the qualitative features of management earnings forecasts could provide a significant signal and illuminate the case of the "missing" firms.

Further, this paper adds evidence to the literature on management earnings forecasts, and particularly to that focusing on the characteristics. In fact, the examination of forecast characteristics and their role as part of a wider disclosure strategy is still an open question (Hirst et al, 2008). I provide evidence that the whole set of guidance characteristics, especially when considered in a multi-period setting, could help predicting firms' future behavior over and beyond the mere, quantitative earnings news.

Finally, this work makes a contribution to the impression management literature. This literature investigates whether firms attempt to portray a more favorable view of their financial performance. I provide evidence on how the structure and the tone of the narrative in management earnings forecasts disclosure explain the subsequent firms' outcome in terms of meeting or missing the market expectations. As such, the study unifies two strands of accounting literature examining word choice and firms' behavior when it comes to reveal the news to analysts and investors.

The rest of the paper is organized as follows. Section 2 discussed the relevant research and outlines plausible predictions. Section 3 describes the data and the research design. Section 4 reports the results from the empirical tests. Section 5 discusses possible implications of the research.

3.2 BACKGROUND AND HYPOTHESES DEVELOPMENT

Analyst forecasts have become the most attractive earnings benchmark, substituting for the traditional targets of positive earnings and previous year earnings (Brown and Caylor 2005; Dechow et al. 2003). Consequentially, the phenomenon of meeting or beating expectations has attracted interest among researchers. Beyer (2008) analytically demonstrates that the capital market response to an earnings surprise is asymmetric since the penalty for a negative earnings surprise is stronger than the reward following a positive earnings surprise. Other empirical papers show that the capital market rewards firms that achieve analyst forecasts and penalizes firms that miss them. Kasznik and McNichols (2002) provide evidence that firms that consistently meet analyst forecasts experience higher market valuations than firms that miss them do. Skinner and Sloan (2002) show that firms with high growth prospectus experience a more profound market reaction to a negative earnings surprise than they do to a positive or no earnings surprise. In their survey, Graham et al. (2005) document that managers fully recognize the implications of meeting or beating analyst forecasts and take actions to avoid a negative earnings news to "build credibility with capital market" by maintaining or increasing stock price. Evidence provided by other studies suggests that both earnings manipulation and expectations management are used to accomplish this objective. Burgstahler and Eames (2006) provide evidence that downward revisions of forecasts occur more frequently when the revision would be sufficient to avoid a negative earnings surprise, suggesting managers' influence on analysts' forecast revisions. Such influence is also documented by Skinner (1997), Kasznik and Lev (1995) and Soffer et al. (2000), who show that companies increasingly tend to warn investors about forthcoming unfavorable earnings. This behavior is consistent with expectations management as a means of meeting/beating the expectations.

Overall these evidence suggests that companies are not merely passive observers in the game of meeting or beating contemporaneous analysts' expectations, however some of them still fall short of market expectations and miss the expected target. The question arises as to which are the factors, beyond the news that the forecast conveys, that could help predict their unfavorable performance, thus their "missing" behavior. To this regard, McAnally et al. (2008) examine whether stock option grants explain missed earnings targets. They find that firms are more likely to miss earnings targets just before large CEO option grants. However, studies investigating whether voluntary disclosure could have explanatory power with respect to firms' missing the market expectations are still absent. In this paper, I conjecture that beyond the news communicated with earnings forecasts, the consistency of a set of attributes and the tone used in the press release forecasts could provide useful insights into future firms' performance and compliance with market expectations. In other words, this study try to establish a link between between firms' missing behavior and the qualitative features of corporate voluntary communication, in the setting of earnings forecasts.

Earnings press releases through which the earnings projections are communicated are "the major news event of the season for many companies as well as investors, analysts, financial media, and the market" (Mahoney and Lewis 2004). They are characterized as a disclosure mechanism revealing a "package of information" to investors (Francis et al. 2002).

An important element of this information package is the set of characteristics with which managers choose to communicate the earnings estimate. Forecast characteristics pertain to the choices that a manager makes relating to the content of the forecast itself, such as its form, the level of disaggregation, and additional information managers may provide (Hirst et al. 2008).

The form (i.e. precision) of the earnings estimate is crucial since it captures the precision of managers' beliefs about the future (King, *et al* 1990). More precise forecasts are generally perceived to reflect greater managerial certainty relative to less-precise forecasts (Hughes and Pae 2004). Factors that are associated with forecasts form include, for example, uncertainty. Baginski and Hassell (1997), using the forecast horizon, document that imprecise forecasts are issued in presence of greater earnings uncertainty.

Managers can also use disaggregation to enhance forecast credibility. Disaggregation reveals forecasted line items of the focal financial statement - the income statement. Disaggregated forecasts of income statement line items are well-defined accounting data (in contrast to other supplementary disclosures, such as qualitative soft talk, that might be neither well-defined nor accounting data). For example, Han and Wild (1991) report that 40% of management earnings guidance is accompanied by revenue guidance and conclude that managers do so when the former is insufficient to reduce the earnings expectation gap between managers and analysts. Lansford et al. (2013) document that 42% of firms issuing forecasts provide disaggregated earnings guidance, consisting of earnings, revenue and specific expenses. Their findings show that disaggregation allows managers to more successfully align analyst expectations with their own and experience more favorable outcomes of meeting or slightly beating earnings.

Another important element of this information package is the language used, which provides the unifying framework within which earnings are announced and other quantitative and qualitative disclosures are made. Prior research on earnings press releases examined the incremental information content of specific, qualitative disclosures like officers' comments. For instance, officers' comments communicating good and bad news about the future are informative above and beyond the announcement of earnings per se (Hoskin, Hughes, and Ricks 1986; Francis et al. 2002). The information revealed to investors via management earnings forecast language, however, likely extends beyond specific officers' comments.

Other research documents that the language in a management forecast affects its usefulness to analysts and investors (as reflected in stock price reactions). For example, language describing forecast precision (e.g., "greater than," "less than," "between," "a record year") is related to stock price reactions to management earnings forecast disclosures (Pownall et al. 1993; Baginski et al. 1993).

In addition, managers often explain their earnings forecasts by linking forecasted performance to their internal actions and the actions of parties external to the firm. These attributions potentially aid investors in the interpretation of management forecasts by confirming known relationships between attributions and profitability or by identifying additional causes that investors should consider when forecasting earnings (Baginski et al. 2004). Consistently with this proposition, promotional language could be observe in press releases, not only in the "officers' comments" sections, but also in the more prevalent non-quotation sections of the release (Maat 2007). In such cases, disclosure narratives provide context for financial data and might convey incremental (not always relevant) information about firm performance (Davis et al., 2012; Loughran and McDonald, 2011; Henry, 2008).

The information content of earnings press releases has increased significantly over time (Francis et al. 2002; Landsman and Maydew 2002) and has been accompanied by a corresponding increase in press release length. Specifically, the number of words used in earnings press releases increased approximately five times between 1980 and 1999 (Francis et al. 2002). This dramatic increase in the sheer number of words used in earnings press releases suggests an important question: Does the language used throughout an earnings press release provide an icremental signal of managers' expectations about future performance and their ability to satisfy market expectations?

The voluntary nature of management forecasts and the accompanying qualitative information, including the tone, place this study as part of a greater investigation of the voluntary disclosure process as a whole. At the same time, companies' future behavior in terms of satisfying the earnings targets finds a linkage, beyond the sole earnings news, with the form and properties of disclosure.

Given the above consideration and the exploratory nature of the research, I do not make directional predictions on single variables and formulate the following predictions.

I first test the probability of missing analyst expectations in period *t+1* respectively on: i) consistency in single characteristics, ii) different types of break in consistency iii) tone. I formalize the following hypotheses:

H1a: The probability of missing the earnings target is associated with consistency in a single characteristic and subsequent changes of the same consistency.

H1b: The probability of missing the earnings target is associated with consistency in a single characteristic, and subsequent positive and negative changes of the same consistency.

H1c: The probability of missing the earnings target is associated with impression management.

Secondly, I test the probability of missing analyst expectations respectively on i) the set of specifications for each characteristic conditional on consistency, ii) tone, iii) word count. I formalize the following hypotheses:

H2a: The probability of missing the earnings target is associated with some of the characteristics specifications, conditional on consistency.

H2b: The probability of missing the earnings target is associated with impression management.

H2c: The probability of missing the earnings target is associated with the total length of the press release earnings forecast.

3.3 DATA AND RESEARCH DESIGN

Sources

Data on analyst forecasts and earnings announcements are obtained from the Institutional Brokers Estimate System (*I/B/E/S)* database. Data on management earnings forecasts are hand-collected from the *Factiva* database using "Press Release Newswire" and "Dow-Jones Business News" sources for the North-America region. Financial data are obtained from Compustat.

Sample selection

The study analyses the universe of US firms for the years 2005-2010. Management earnings forecasts are hand-collected from press releases. I download candidate management earnings forecasts through Factiva and perform a search of the following keywords: *"expects earnings", "expects net", "expects income", "expects losses", "expects profits", and "expects results"*, plus three parallel lists where "*expects"* is replaced alternatively by *"forecasts", "predicts", and "sees"* (Baginski et al. 2004). This search yields 9,304 candidate earnings forecasts observations downloaded in batches of 100 announcements per .txt file and corresponding to 2,505 firms' observations. The press release is treated as unit of observation. Each company identifier (referred as to "CO" in Factiva) is extracted from the downloaded text and, through a textual algorithm, matched to the common Compustat company name and ticker identifier. I manually verify these automated "candidate matches". After a first screening of the reported headlines, 535 press releases are deleted as they do not refer to companies' future earnings but to "footnotes", "recap", “correction”, “market talk” or appear to be generic. Following Gong et al. (2011), I exclude guidance issued in prior years if already existing for the current year because these long-term forecasts contain more uncertainty, and are not comparable to forecasts issued during the current period. This process yielded a total of 5,434 forecast observations, corresponding to 1,603 firms observations. Only the annual subsample is considered, which yields a total of 2,263 earnings forecast observations corresponding to 946 firms. Finally, I require sample firms to exist in the Compustat and I/B/E/S database, leading to a final sample of 1,104 observations.

Each press release is then content analyzed. The forecast’s characteristics information is manually reported as well as the number of positive and negative words.

Measures of consistency

For the purpose of this study the predictions are tested on annual earnings forecasts consistent with Tang (2012), although this can limit the sample size, and involve two different types of consistency measures. The first type captures the consistency for each of the characteristics I observed, thus providing insight into the specific role of them. More precisely, three characteristics are taken from previous literature[21] and defined as:

- Precision: which articulates in “point”, “range”, “open-ended”, “qualitative”;
- Level of disaggregation: which articulates in “earnings news only”, “earnings and revenue or sale items”, “earnings and at least one major expense” and “earnings and detailed income statements/balance sheet items”;
- Additional qualitative information: which articulates in “earnings explanation” (either internal or external attributions), “CEO comment” and “update”

[21] For an extended review of the topic see Hirst et al. (2008).

I code the three dimensions as consistent for a given firm if they are unchanged from one fiscal year (*t-1*) to the other (*t*). This requires earnings forecasts to exist for at least two consecutive years. I assume that firms providing annual guidance with a certain set of characteristics at year *t-1* will be prone to provide a guidance at year *t* which reflects the previous one in terms of characteristics composition.

The second type of measure captures the specification of each characteristic conditional on consistency. The specifications articulate as following:

- 1) point, 2) range, 3) open-ended, and 4) qualitative, for the level of precision.
- 1) earnings only , 2) earnings plus revenues or sales, 3) earnings plus at least one major expense 4) earnings plus expenses, for the level of disaggregation.
- 1) “CEO comment”, 2) “update”, 3) “earnings explanation”, for the type of additional qualitative information.

As for both measurements, I classify firms as “consistent” based on persistence of the characteristic or specification over time. I assigned a total score at each firm-year based on the characteristic/specification to which consistency applies and bond its definition to preceding fiscal year irrespective of a sequence of quarters. This allows to draw inferences on the role and importance of each of the forecasts’ attributes and specifications.

I create three indicator variables, one for each characteristic, and replicate the measures for the specifications of characteristics. The resulting variables are defined as follows:

- *CONS_PREC*: refers to an indicator variable equal to 1 when the forecast display an identical level of precision (irrespective of the specification on which the earnings forecast is consistent - i.e. point, range, qualitative -), from one period to the other, 0 otherwise.
- *CONS_DISAG*: refers to an indicator variable equal to 1 when the forecast display an identical level of disaggregation (irrespective of the specification on which the earnings

forecast is consistent - i.e. earnings only, revenues or sale, at least one major expense, other expenses -), from one period to the other, 0 otherwise.

- *CONS_ADD*: refers to an indicator variable equal to 1 when the forecast display the same type of qualitative information (irrespective of the specification on which the earnings forecast is consistent - i.e. earnings explanation, CEO/CFO comment, update -), from one period to the other, 0 otherwise.
- *CONS_POINT* = indicator variable equal to 1 if the forecast displays a point estimate from one period to the other (i.e. for two consecutive periods), 0 otherwise.
- *CONS_RANGE* = indicator variable equal to 1 if the forecast displays a range estimate from one period to the other (i.e. for two consecutive periods), 0 otherwise.
- *CONS_QUAL* = indicator variable equal to 1 if the forecast displays a qualitative estimate from one period to the other (i.e. for two consecutive periods), 0 otherwise.
- *CONS_EARN_ONLY* = indicator variable equal to 1 if the forecast displays the earnings estimate only from one period to the other (i.e. for two consecutive periods), 0 otherwise.
- *CONS_REVENUE* = indicator variable equal to 1 if the forecast displays the earnings estimate plus an estimate for revenues or sales from one period to the other (i.e. for two consecutive periods), 0 otherwise.
- *CONS_EXPENSES* = indicator variable equal to 1 if the forecast displays the earnings estimate plus an estimate for at least one major expense (i.e. for two consecutive periods), 0 otherwise.
- *CONS_CEO_COMM* = indicator variable equal to 1 if the forecast displays a CEO/CFO comment (i.e. for two consecutive periods), 0 otherwise.
- *CONS_UPDATE* = indicator variable equal to 1 if the forecast displays an update of the earnings projection from one period to the other (i.e. for two consecutive periods), 0 otherwise.

- *CONS_EXPLANATION* = indicator variable equal to 1 if the forecast displays an earnings explanation (i.e. either internal or external attributions) from one period to the other (i.e. for two consecutive periods), 0 otherwise.

When a pattern of consistent characteristics is interrupted because of a change in one or more of them, we are in presence of a potential "break" that can affect the level of information asymmetry. On the one hand, it can be the case of moving from a condition *x* of "given level of detail" to a condition *y* of "increasing level of detail" (i.e. from lev 1 disaggregation to lev 2), thus a positive change is registered. Conversely, when one or more characteristics are changing from a condition *x* to a "decreasing level of detail" (i.e. from lev 2 disaggregation to lev 0), a negative change is registered. I code each MEF as having a break in consistency if the firm after being consistent with respect to the previous period still provide a forecast but with different characteristics in terms of precision, disaggregation and additional information, thus interrupting the pattern. This requires a forecast to exist for at least three consecutive years. I first use an aggregated measure of break, then I examine positive and negative breaks separately.

I capture the change and define the measures as follows:

- *BREAK_PREC*: refers to an indicator variable equal to 1 when the forecast has been classified as consistent with respect to the previous period (*t*-1) but display a different level of precision (point, range, open-end, qualitative) for the current period, 0 otherwise.
- *BREAK_DISAG*: refers to an indicator variable equal to 1 when the forecast has been classified as consistent with respect to the previous period (*t*-1) but display a different level of disaggregation (earnings only, earnings and revenues or sale, earnings and at least one major expense, earnings and detailed line items) for the current period, 0 otherwise.
- *BREAK_ADD*: refers to an indicator variable equal to 1 when the forecast has been classified as consistent with respect to the previous period (*t*-1) but display a different type

of additional qualitative information (earnings explanation, CEO/CFO comment, update) for the current period, 0 otherwise.

Impression Management Measure

In general, common capital markets research trying to evaluate the market implications of qualitative financial disclosure, relied on human coders and produced an "item-by-item subjective assessments of tone" as outcome (Francis et al.1994; Lang and Lundholm 2000; Francis et al. 2002). These days, computational linguistics is a well-known and established discipline in various field, not only in management and represents an effective tool when it comes to capture the content of an entire document. The approach allows each document to be treated as a set of words and is based on a count of the relative frequency with which some words of interest appear. Frequency counts of words are employed to explore the content of textual communication as well as to measure the tona of a text and other alternative attributes. In order to capture the tone accompanying a document, a word lists containing both positive and negative words of reference need to be constructed. Secondly, it involves the count of the number of times these words appear in the text under analysis.

To proxy for the content that managers want to communicate, I define the tone score as follows (Henry and Leone, 2009):

(Positive–Negative)/(Positive+Negative)

Where:

- *POSITIVE* is the frequency of occurrences in an earnings press release of words in the positive wordlist;
- *NEGATIVE* is the frequency count of occurrences of words in the negative wordlist.

Davis et al. (2007) define *POSITIVE* and *NEGATIVE* as the percentage of positive and negative words respectively, while Rogers et al. (2009) measure tone as the difference between the counts of positive and negative words, scaled by total words. I use alternative measure of tone as robustness in additional analysis to validate the impression management score and my results.

Among the most widely used wordlist to categorize words are Diction, developed in the domain of social psychology, and GI. According to Kothari et al. (2009), who use the GI positive and negative wordlists, the content of narrative disclosure exerts significant influence on analysts' forecasts dispersion. In their analysis of MD&A sections and financial footnotes of 10-K and 10-Q SEC files, they notice that favorable news reduce analysts' forecasts dispersion while unfavorable news exerts the opposite effect. Tetlock et al. (2008) observe that the explanatory power of tone persists even if stock returns of the same period are considered as proxy for all other relevant information disclosed. They infer in this manner the ability of negative tone to represent other negative attributes of firm's environment, thus catching incremental measures of firm's fundamentals.

Davis et al. (2007) find a relation between the market reaction to earnings announcements and the unexpected tone of the announcement. Rogers et al. (2009), using Diction positive and negative wordlists, find that the tone of sued firms' disclosures is more positive than that of a matched sample of non-sued firms, and suggest that the use of more positive language increases the likelihood of being sued.

One potential concern deriving from the use of positive and negative word lists from GI and Diction is related to the domain specific words used in accounting and financial disclosure. As a consequence, the broad wordlists provided by these common softwares likely lack effectiveness ad predictive power in capital markets setting. For example, the GI wordlist contains words that are irrelevant to financial communication, like: "amazing", and it omits the words "record" and "strong", which are for example used in earnings announcements related research (Henry 2008). In addition, the categorization of a number of words as positive or negative in the general domain wordlists is based on one meaning of the word, although the words could have different meanings in the financial disclosure literature. For instance, GI categorizes the word “division” as negative, but in most financial disclosure this word describes a segment of a company and would be neither negative nor positive (Henry, 2008). An alternative method is to make use of word drawn from domain-specific list. To this end, Henry (2006, 2008) constructs a wordlist intended for financial disclosure usage purposes and demonstrates its effective validity in the setting of the earnings announcements. Henry’s (2006) finds that word count measures of qualitative information in earnings announcements improve prediction of firm’s returns following the announcement. Further, Henry (2008) document that the tone of qualitative information in earnings press release has a positive, nonlinear relation with cumulative abnormal returns during the three-day event window around the earnings announcement. Finally, Henry and Leone (2009) using a sample of over 15,000 earnings press releases show that the domain-specific wordlist developed by Henry (2006, 2008) represents a more powerful tool than the common wordlists used in past research.

Empirical Design

To test the hypotheses and see whether the measures that I identify as proxies for consistency in earnings guidance characteristics and for impression management have some predictive power in explaining firm’s failure to meet market expectations one year ahead, I employ the following empirical design. I estimate a logistic model using the probability that the firms misses analyst expectations in the future as dependent variable. All the continuous variables are winsorized at the 1th and 99th percentile. The coefficients resulting from the estimations are tested using the Wald test, which lead to reject the null hypothesis that they are simultaneously equal to zero. Different measures of fit have been calculate in order to test whether each of the model used is adequate, although this cannot ensure that selecting a model that maximize the value of a given measure results in a model that is optimal in any sense.

The main control variables included in the models reflect: whether firms meet or beat analyst expectations in the current period, firm' performance, the earnings surprise, size, leverage and industry. Variable definitions are listed in the Appendix.

The logistic models implemented are illustrated below:

Model 1

$$Pr\ (MISS\_POST) = \alpha_0 + \alpha_1\ CONSISTENCY_{it} + \alpha_2\ BREAK_{it} + \alpha_3\ CHAR\_LEV0_{it} + \alpha_4\ MEET_{it} + \alpha_5\ ROA_{it} + \\ + \alpha_6\ EARN\_DIFF\ _{it} + \alpha_7\ SIZE_{it} + \alpha_8\ LEV_{it} + \alpha_9\ INDUSTRY_{it} + \varepsilon.$$

Model 2

$$Pr\ (MISS\_POST) = \alpha_0 + \alpha_1\ CONSISTENCY_{it} + \alpha_2\ BREAK\_POS_{it} + \alpha_3\ BREAK\_NEG_{it} + \alpha_4\ CHAR\_LEV0_{it} + \\ + \alpha_5\ MEET_{it} + \alpha_6\ ROA_{it} + \alpha_7\ EARN\_DIFF_{it} + \alpha_8\ SIZE_{it} + \alpha_9\ LEV_{it} + \alpha_{10}\ INDUSTRY_{it} + \varepsilon.$$

Model 3

$$Pr\ (MISS\_POST) = \alpha_0 + \alpha_1\ TONE_{it} + \alpha_2\ CHAR\_LEV0_{it} + \alpha_3\ MEET_{it} + ROA_{it} + \alpha_5\ EARN\_DIFF_{it} + \alpha_6\ SIZE_{it} \\ + \alpha_7\ LEV_{it} + \alpha_8\ INDUSTRY_{it} + \varepsilon.$$

Model 4

$$Pr\ (MISS\_POST) = \alpha_0 + \alpha_1\ CONSISTENCY_{it} + \alpha_2\ BREAK\_POS_{it} + \alpha_3\ BREAK\_NEG_{it} + \alpha_4\ TONE_{it} \\ + \alpha_5\ CHAR\_LEV0_{it} + \alpha_6\ MEET_{it} + \alpha_7\ ROA_{it} + \alpha_8\ EARN\_DIFF_{it} + \alpha_9\ SIZE_{it} + \\ + \alpha_{10}\ LEV_{it} + \alpha_{11}\ INDUSTRY_{it} + \varepsilon.$$

Model 5

$$Pr\ (MISS\_POST) = \alpha_0 + \alpha_1\ CONS\_SPEC\_1_{it} + \alpha_2\ CONS\_SPEC\_2_{it} + \alpha_3\ MEET_{it} + \alpha_4\ ROA_{it} + \\ + \alpha_5\ EARN\_DIFF_{it} + \alpha_6\ SIZE_{it} + \alpha_7\ LEV_{it} + \alpha_8\ INDUSTRY_{it} + \varepsilon.$$

Model 6

$$Pr\ (MISS\_POST) = \alpha_0 + \alpha_1\ CONS\_SPEC\_1_{it} + \alpha_2\ CONS\_SPEC\_2_{it} + \alpha_3\ TONE_{it} + \alpha_4\ MEET_{it} + \alpha_5\ ROA_{it} + \\ + \alpha_6\ EARN\_DIFF_{it} + \alpha_7\ SIZE_{it} + \alpha_8\ LEV + \alpha_9\ INDUSTRY_{it} + \varepsilon.$$

Model 7

$$Pr\ (MISS\_POST) = \alpha_0 + \alpha_1\ CONS\_SPEC\_1_{it} + \alpha_2\ CONS\_SPEC\_2_{it} + \alpha_3\ TONE_{it} + \alpha_4\ WC_{it} + \alpha_5\ MEET_{it} + \\ + \alpha_6\ ROA_{it} + \alpha_7\ EARN\_DIFF_{it} + \alpha_8\ SIZE + \alpha_9\ LEV_{it} + \alpha_9\ INDUSTRY_{it} + \varepsilon.$$

3.4 RESULTS

Descriptive Statistics

Panel A of Table 1 illustrates the distribution of firms missing the earnings target by year.

[INSERT TABLE 1 HERE]

The higher number of observations is concentrated in years 2006 and 2007, while the last two sample years, 2009 and 2010, account for a scarce/null percentage. Panel B shows the distribution of firms missing the earnings target by industry. The industry with the higher percentage of missing firms are respectively "other" (financial institutions included) and "shops and retail", followed by "healthcare".

Table 2 presents information related to the distribution of each forecast characteristics.

[INSERT TABLE 2 HERE]

Panel A shows that the vast majority of annual forecasts are issued in a range format (76.63%), 11.96% of the observations are qualitative forecasts and 9.42% are numerical point estimates, while only 1.99% are open-ended. Panel B shows that the management forecasts at minimum provide the earnings projection (level 0 disaggregation), more than half of the sample provide the revenue or sale items information (level 1 disaggregation), 15.49% accompany earnings with at least one major expense line item (level 2 disaggregation), while only 1.45% show more detailed line items (level 3 disaggregation)[22]. Panel C gives some information about the additional qualitative information. One quarter of the forecasts in the sample is bounded with CEO or CFO comments; 13.86% provide an explanation for the earnings estimate (of which 66.67% rely on internal attributions, while 51.63% on external attributions). Finally, almost one third of observations could be referred as to earnings estimate updates.

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[22] For purpose of analysis, disaggregation at level 2 and at level 3 are then combined into one unique score as I am interested in firms who make disclosure of their expenses, independently of the type and quantity of expenses provided. I believe it could be reasonable to extend the category to all firms disaggregating at the expense level as the only requirement to be included is the disclosure of at least one expense.

Table 3 reports data related to the distribution of the consistency measures and changes in consistency.

[INSERT TABLE 3 HERE]

Panel A shows that, in terms of single-characteristic measures, 23.64% of the sample is consistent in precision, 18.39% in disaggregation and 10.69% in the type of additional information given. In terms of specification of each characteristic, for precision the highest percentage is made of consistent range forecasts, while for disaggregation of consistent "earnings only" (i.e. level 0) forecasts. For additional information, the majority of firms are consistent in giving no supplementary information, however among the ones that provide it, the earnings update is the most common additional disclosure. Panel B describes the distribution of breaks and the type (i.e. positive vs negative) after a firm has issued forecasts with identical attributes for two years: 61% of consistent firms show a break in precision with the most being negative breaks (96.88%), 4.93% show a break in disaggregation (40% positive and 60% negative), and 17.80% show a break in additional information provided with a 66.67% of negative breaks.

Panel A of Table 4 reports the distribution (mean and median) of positive and negative keywords by year.

[INSERT TABLE 4 HERE]

The mean length of the press releases is 881.35 words, with a median value of 378. The content of management earnings forecasts generally reflects positive information across years. In addition, the number of both positive and negative keywords has been increasing starting 2007. This is in line with the steady increase starting from 2007 of the total length of companies' press releases (see also Francis et al. 2002). Panel B illustrates the distribution (mean and median) of positive and negative keywords by categories of consistency. For firms showing consistency in precision, disaggregation or additional information the average forecast's length range from 447 to 492 words. The content reflects positive information across years. Noticeable is then the higher number of total words for firms who are consistent in providing qualitative earnings, disaggregating at the expenses level and supplement forecasts with the explanation of the earnings estimate. Further, both the consistency in qualitative earnings and explanations show almost a fair distribution between positive and negative words.

Table 5 summarizes the descriptive statistics of the main variables included in the models.

[INSERT TABLE 5 HERE]

On average one firm out of four in the sample misses the analyst expectation. The measure of tone, based on Henry's (2006) list of keyword, has a mean of 0.41, and is positive from the second quintile, indicating that management forecasts contain significantly more positive content than negative. Firms tend to be bigger with a mean of 7.5 million sales and profitable with an average return on assets of 5%.

Table 6 Panel A and B report Pearson correlations.

[INSERT TABLE 6 HERE]

Panel A shows the correlation among the consistency measures and breaks. Panel A indicates that the consistency measures based on single characteristic are positively correlated. Correlations in all three cases are less than 1, meaning that each measure contains different information. The specifications of precision (conditional on consistency) show very low correlations. The same low correlations are also shown for the different specifications of both disaggregation and additional information. Panel B reports Pearson correlations of the variables included in the models. Interestingly, the consistency in qualitative earnings (for precision) and in expenses (for disaggregation) and the word count are positively and significantly correlated to miss_post. The tone is also significantly correlated to miss_post even if negatively.

Empirical Results for H1 and H2

As discussed above, H1a focuses on the effect of consistency in a single characteristic and the related break on the probability of missing the earnings target in the subsequent year. H2a looks at the effect of break distinguishing between positive (i.e. transition from a given level of detail to an increasing level of detail - from range to point, etc…) and negative (i.e. transition from a given level of detail to a decreasing level of detail - from range to qualitative, etc…). H3a introduces a hypothetical association between the tone of the press release and the probability of missing the target. H4a involves the test of the effects of all these variable in an augmented model. I use *miss_post* as the dependent variable. I run four separate logistic models and repeat the analysis for each of the three characteristics – precision, disaggregation and additional information.

Table 7 reports tabulated results of the effect of consistency in precision on the probability of missing the target in the subsequent period.

[INSERT TABLE 7 HERE]

The coefficient on *consistency* is positive and significant (z-stat 2.56), while the coefficient on break is negative and significant (z-stat 2.06). In model 2, consistency loads positively and significantly (z-stat 2.56), while the effect of breaks remains negative and significant but only for negative breaks. Model 3 shows that *tone* is negatively related to *miss_post* and the coefficient is significant (z-stat 2.48). In model 4, the augmented regression, both *consistency* in precision and *tone* keep their significance as well as the sign, while *break_neg* becomes only marginally significant. The control variables show the expected sign even though only *meet*, *roa*, *size* and *leverage* are significant.

Table 8 reports the four logit regressions in the case of disaggregation.

[INSERT TABLE 8 HERE]

The coefficient on *consistency* is positive and significant (z-stat 2.22), while the coefficient on break is not significant. In model 2, consistency loads positively and significantly (z-stat 2.22), but nor the coefficient on positive neither the one on negative breaks are significant. The tone regression confirms a negative and significant association (z-stat 2.23). When combined in a single model (model 4), again consistency and tone are the only variables that keep their sign and significance (z-stat 2.28; 2.23). Also in this case, the control variables show the expected sign even though only *meet, roa*, *size* and *leverage* are significant.

Table 9 reports tabulated results for the third characteristic: additional information.

[INSERT TABLE 9 HERE]

The coefficients on consistency and break in model 1 are not significant, and so are the coefficients on positive and negative break in model 2. The results in model 3 document a negative and significant association (z-stat 2.45) of tone with the dependent variable miss_post. The coefficients in model 4 confirm the latter results, tone loads significantly negatively (z-stat 2.49), while consistency and break are not significant.

Overall, the first set of findings suggest that forecast's consistency (in precision and disaggregation) and tone do incorporate explanatory power with respect to the subsequent event of firms missing the earnings target, thus providing support for the first set of hypotheses.

The evidence reveal that firms falling short of the earnings expectations are accompanied by a history of consistent guidance characteristics and the negative coefficient on "*break*" is also confirming it. The hypotheses find further support when it comes to the effect of the type of break in the case of precision. The transition to a characteristic's specification providing a decreasing level of detail (i.e. from point to range, etc…), after a consistent pattern, negatively affects the probability of missing the target. This, once again, suggests that the firm would not change its forecasts' pattern, especially if the change is negatively influencing the level of detail provided, thus increasing information asymmetry.

On the other hand, firms are not taking advantage of impression management techniques as to inflate expectations, suggesting that they probably don't have incentives at doing so. Instead they act as anticipating uncertainty and negative outcomes surrounding the future news. Taken together, the results suggest that firms that is going to miss the target tend to be sticky to their forecasts' characteristics pattern and do not make use of impression management when disclosing future earnings estimates in the previous period.

I reasonably expect that firms acting as keeping their forecasts unchanged and warning investors about forthcoming unfavorable earnings are not the only that are going to miss the earnings target. They could even be the ones that exactly meet or just beat expectations due to the greater likelihood of managerial intervention (i.e., earnings or expectations management, see Burgstahler and Eames 2006). Given the objective of this study, I am aware of this limitation and acknowledge that the paper will benefit from further analysis and extensions, perhaps selecting a control group of firms that has been shown to practice expectation management.

The second set of hypotheses focuses on the investigation of the effects of characteristics' specifications (conditional on consistency) and impression management on the probability of firms' missing future earnings targets. Table 10 presents the results from estimating regression model 5, 6 and 7 for the set of specifications of precision.

[INSERT TABLE 10 HERE]

Model 5 shows that the coefficient on *cons_range* is negative and significant (z-stat 2.45), while the coefficient on *cons_point* is negative but marginally significant (z-stat 1.93). Notably, when looking at the intercept, which captures the residual specification (i.e. qualitative earnings) of the dummy variables for consistency, this is positive and significant (z-stat 2.21). When tone is included in the regression (model 6), the negative coefficients on *cons_point* and *cons_ range* become only marginally significant, while the intercept is still positive and significant at the 0.01 level (z-stat 2.94). The coefficient on tone is negative and marginally significant. Model 7 reports the results for the regression including *wc*. The main coefficients remain significant with unchanged sign and *wc* loads positively and significantly even though the magnitude of the coefficient is small. All the control variables go in the expected directions, although only *size* is significant at the 0.01 level.

Table 11 illustrates the results for the specifications of disaggregation.

[INSERT TABLE 11 HERE]

Model 5 shows that the coefficient on *cons_revenue* is negative and significant (z-stat 2.69), and the coefficient on the intercept, which captures the residual specification (i.e. disaggregation at the expenses level) of the dummy variables for consistency, is positive and significant at the 0.01 level (z-stat 3.63). When tone is included in the regression (model 6), the coefficients on *cons_point* and intercept remain significant with no sign change. The coefficient on *tone* is negative but not significant. Also after *wc* is included, *tone* is not significant. This result most likely appears to be contingent on the drop in the sample size once I conditioned for consistency, indeed the robustness of inferences from logistic regression is dependent on sample size. The control variables display the expected sign, although only *roa* and *size* are significant.

Table 12 presents the results for the specifications of additional information.

[INSERT TABLE 12 HERE]

Consistent firms accompanying the earnings estimates with an explanation experience a higher probability of missing the earnings target in the subsequent period, as documented by the positive sign and significance (z-stat 2.62) of the coefficient on the intercept in model 5. *Cons_ceo_comm*, conversely, displays a negative and significant coefficient (z-stat 2.00). When *tone* is added to the model, it shows a negative but insignificant coefficient. The result doesn't change after including *wc* to the model. The control variables go in the expected directions and are significant, except for *leverage*.

On the whole, the results suggest that management earnings forecasts' qualitative attributes are an important source of information with respect to future probability that a firm misses the earnings expectation. A consistent disclosure policy in terms of earnings forecasts' characteristics is viewed by firms as a strategic decision, especially in presence of bad news, as not to influence analyst expectations about the private information managers possess. Indeed, analysts and investors cannot perfectly anticipate the relation between what management knows and what they disclose. More interestingly, when examining the different specifications of consistency, managers of firms that are going to miss the earnings targets tend to be consistent on qualitative earnings, on disaggregation at the expenses level and on providing an explanation for the future earnings projection.

Further, the tone used is not directed at managing or creating expectations, instead it progressively reveal either negative events or the bad news itself, supporting management's weaker incentives to manipulate beliefs through disclosure choices. We can thus infer that the qualitative features of management earnings forecast disclosure are more likely part of an overall disclosure package, which is not limited to a single time period but goes beyond that in a sort of dynamic cycle. The qualitative form of earnings allows managers to reveal the lowest amount of details regarding future earnings, thus keeping information private or hiding the lack of private information to the market. At the same time, they also satisfy the expectations of the market thanks to the release of the information itself (i.e. the fact that the press release exists). On the other hand, being consistent in disaggregating at the expense level allows managers to provide whatsoever information regarding the costs that are expected to negatively influence the firm' prospects, as well as being consistent on giving an earnings explanation could help investors in the interpretation of management forecasts by confirming known relationships between attributions and profitability, or by identifying additional causes that investors and analysts should consider.

3.5 ADDITIONAL ANALYSIS

Alternative measures of tone

To capture the disclosure tone accompanying the earnings announcement, I use the degree of net optimism, a commonly used measure in computational linguistics to proxy for the message management desires to communicate. Net optimism is defined as the number of optimistic words less the number of pessimistic words in the passage of text under study scaled by their total sum. However, for comparability to prior literature, I examine also the "positivity" and "negativity" scores, computed as "*POSITIVE/TOTAL WORD COUNT"* and "*NEGATIVE/TOTAL WORD COUNT*". When substituting the measure of tone with the latter, the positivity score is negative and not significant across models, while the negativity score show positive and significant coefficients. These results confirm previous inferences.

Alternative word lists

The word lists employed in the primary analysis are those derived by Henry (2006) and subsequently used in Henry and Leone (2009). To ensure that the choice of a particular set of word lists is not driving my results, I compute the measure of tone using an alternative set of word lists, employed by Loughran and McDonald (2010). Untabulated results shows qualitative similar statistical inferences obtained when using the latter.

3.6 CONCLUSIVE REMARKS

This paper examines whether qualitative features of management earnings forecasts have predictive power in explaining firms' missing the earnings target. More precisely, I explore whether the consistency in guidance characteristics and the tone accompanying the earnings projections can significantly predict the probability that a firm misses financial analyst forecasts in the subsequent period.

First, I focus on the role of consistency in single characteristics and tone separately. Secondly, I augment the regression model in order to observe the incremental effect of the two. Next, I focus on the role of each characteristic's specification conditional consistency and tone. I run a separate regression for the consistency measures and progressively include the impression management score and a variable for the total document's word count.

I find that consistency in precision and disaggregation positively influence the probability of missing the target in the subsequent year, while the impression management score is negatively related to it. When examining the different specifications of consistency, managers of firms that are going to miss the earnings targets tend to be consistent on qualitative earnings, on disaggregation at the expenses level and on providing an explanation for the future earnings projection. The tone used is not directed at managing expectations, instead progressively reveal either negative events or the bad news itself supporting management's weaker incentives to manipulate beliefs through impression management choices. Overall the results suggest that management earnings forecasts' qualitative attributes are an important source of information with respect to the future probability of firms' missing the earnings expectation.

The paper contributes to the literature in three aspects. First it represents an incremental contribution to the collective understanding of firms' phenomenon of missing the earnings target. Considerable research explores the "meet or beat" phenomenon, however the examination of the disclosure factors that can predict a firm missing the earnings expectation is still an open issue. The paper also adds to the literature on management earnings forecasts, and particularly to that focusing on the characteristics of the latter. I provide evidence that the whole set of guidance characteristics, especially when considered in a multi-period setting, could help predicting firms' future behavior over and beyond the mere earnings news. Finally, the study make a contribution to the impression management literature. This literature investigates whether firms attempt to portray a more favorable view of their financial performance. I provide evidence on how the structure and the tone of the narrative in management earnings forecasts disclosure could explain the subsequent firms' outcome in terms of meeting or missing the market expectations. As such, the study unifies different strands of accounting literature examining a firm's qualitative disclosure and its behavior when it comes to reveal the earnings news.

The results should be of interest to academics who study corporate voluntary disclosure, as well as to practitioners and managers who are choosing firms' disclosure policies. Further research is needed to fully address the issue, especially to explore in which aspect firms that miss the target differ from firms intentionally doing so or firms walking down to a beatable target, and to exclude reverse causality.

APPENDIX

Variable Definitions

<u>Missing Firms</u>

***MISS_POST** = indicator variable equal to 1 if the firm misses analyst consensus forecasts in the subsequent period with respect to the one in which the firm is observed, 0 otherwise.*

<u>Consistency measures</u>

***CONS_PREC** = indicator variable equal to 1 if the forecast displays an identical level of precision (point, range, open-end, qualitative) from one period to the other, 0 otherwise.*

***CONS_DISAG** = indicator variable equal to 1 if the forecast displays an identical level of disaggregation (earnings only, revenues or sale, at least one major expense, other) from one period to the other, 0 otherwise.*

***CONS_ADD** = indicator variable equal to 1 if the forecast displays the same type of qualitative information (earnings explanation, CEO/CFO comment, update) from one period to the other, 0 otherwise.*

***BREAK_PREC** = an indicator variable equal to 1 when the forecast has been classified as consistent with respect to the previous period (t-1) but display a different level of precision (point, range, open-end, qualitative) for the subsequent period, 0 otherwise.*

***BREAK_PREC_POS** = an indicator variable equal to 1 when the forecast has been classified as consistent with respect to the previous period (t-1), but display a positive change[23] in the level of precision (i.e. from qualitative to range, or from range to point etc…) at year t+1 with respect to year t, 0 otherwise.*

***BREAK_PREC_NEG** = an indicator variable equal to 1 when the forecast has been classified as consistent with respect to the previous period (t-1), but display a negative change[24] in the level of precision (i.e. from point to range, or from range to qualitative etc…) at year t+1 with respect to year t, 0 otherwise.*

***BREAK_DISAG** = an indicator variable equal to 1 when the forecast has been classified as consistent with respect to the previous period (t-1) but display a different level of disaggregation (earnings only, revenues or sale, at least one major expense, other) for the subsequent period, 0 otherwise.*

***BREAK_DISAG_POS** = an indicator variable equal to 1 when the forecast has been classified as consistent with respect to the previous period (t-1), but display a positive change in the level of disaggregation (i.e. from level 0 to level 1, or from level 1 to level 2 etc…) at year t+1 with respect to year t, 0 otherwise.*

***BREAK_DISAG_NEG** = an indicator variable equal to 1 when the forecast has been classified as consistent with respect to the previous period (t-1), but display a negative change in the level of disaggregation (i.e. from level 2 to level 1, or from level 1 to level 0 etc …) at year t+1 with respect to year t, 0 otherwise.*

***BREAK_ADD** = an indicator variable equal to 1 when the forecast has been classified as consistent with respect to the previous period (t-1) but display a different level of additional information (earnings explanation, CEO/CFO comment, update) for the subsequent period, 0 otherwise.*

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[23] In other words, the change adds level of detail within the same characteristic.
[24] In other words, the change reduces level of detail within the same characteristic.

BREAK_ADD_POS *= an indicator variable equal to 1 when the forecast has been classified as consistent with respect to the previous period (t-1), but display a positive change in the level of additional information (i.e. from providing a CEO comment to providing a CEO comment plus an explanation etc…) at year t+1 with respect to year t, 0 otherwise.*

BREAK_ADD_NEG *= an indicator variable equal to 1 when the forecast has been classified as consistent with respect to the previous period (t-1), but display a negative change in the level of additional information (i.e. from providing a CEO comment plus an update to providing only a CEO comment etc …) at year t+1 with respect to year t, 0 otherwise.*

CONS_POINT *= indicator variable equal to 1 if the forecast displays a point estimate from one period to the other (i.e. for two consecutive periods), 0 otherwise.*

CONS_RANGE *= indicator variable equal to 1 if the forecast displays a range estimate from one period to the other (i.e. for two consecutive periods), 0 otherwise.*

CONS_QUAL *= indicator variable equal to 1 if the forecast displays a qualitative estimate from one period to the other (i.e. for two consecutive periods), 0 otherwise.*

CONS_EARN_ONLY *= indicator variable equal to 1 if the forecast displays the earnings estimate only from one period to the other (i.e. for two consecutive periods), 0 otherwise.*

CONS_REVENUE *= indicator variable equal to 1 if the forecast displays the earnings estimate plus an estimate for revenues or sales from one period to the other (i.e. for two consecutive periods), 0 otherwise.*

CONS_EXPENSES *= indicator variable equal to 1 if the forecast displays the earnings estimate plus an estimate for at least one major expense (i.e. for two consecutive periods), 0 otherwise.*

CONS_CEO_COMM *= indicator variable equal to 1 if the forecast displays a CEO/CFO comment (i.e. for two consecutive periods), 0 otherwise.*

CONS_UPDATE *= indicator variable equal to 1 if the forecast displays an update of the earnings projection from one period to the other (i.e. for two consecutive periods), 0 otherwise.*

CONS_EXPLANATION *= indicator variable equal to 1 if the forecast displays an earnings explanation (i.e. either internal or external attributions) from one period to the other (i.e. for two consecutive periods), 0 otherwise.*

<u>Impression Management</u>

TONE *= Number of positive words less the number of negative words scaled by the sum of positive and negative words in the earnings press release using the dictionary developed by Henri(2006)*

WC *= Total number of words in the press release*

<u>Other Guidance Variables</u>

CODE_PREC_T0 *= specification of precision (i.e. point, range, open ended, qualitative) at the initial stage from which consistency is measured.*

CODE_DISAG_T0 *= specification of disaggregation (i.e. level 0, level 1, level2 or level3) at the initial stage from which consistency is measured.*

CODE_ADD_T0 *= specification of additional qualitative information (i.e. CEO comment, update, explanation) at the initial stage from which consistency is measured.*

MEET *= indicator variable equal to 1 if realized annual EPS is greater than or equal to analysts' consensus forecasts in year t, 0 otherwise.*

<u>*Firm Performance*</u>

ROA*= return on assets in year t-1*

<u>*Control variables*</u>

EARN_DIFF *= Absolute value of the difference between realized EPS in year t-1 and realized EPS in year t scaled by realized EPS in year t.*

SALE GROWTH*=difference between sales in year t and sales in year t-1 scaled by sales in year t-1*

SIZE *= natural log of total sales in year t*

LEV *= ratio of total debt over total assets at the end of year t-1*

INDUSTRY *= industry classification based on the 10 Fama-French*

Table 1: Distribution of firms missing the target in the subsequent year

Panel A

By year	**Frequency (Obs.)**	**Percent**
2004	11	4.00
2005	57	20.73
2006	66	24.00
2007	75	27.27
2008	40	14.55
2009	26	9.45
2010	0	0
Total	275	100

Panel B

By industry	**Frequency (Obs.)**	**Percent**
Consumer Non-Durables	20	7.27
Consumer Durables	14	5.09
Manufacturing	29	10.55
Energy	12	4.36
Hi-Tech	30	10.91
Telecom	3	1.09
Shops/Retail	47	17.09
Healthcare	34	12.36
Utilities	25	9.09
Other (finance included)	61	22.18
Total	275	100

Table 2: Distribution of the characteristics

Panel A

By forecast precision	Frequency	Percent
Point	104	9.42
Range	846	76.63
Open End	22	1.99
Qualitative	132	11.96
Total	1,104	100

Panel B

By forecast disaggregation	Frequency	Percent
Level 0	1,104	100
Level 1	593	53.71
Level 2	171	15.49
Level 3	16	1.45
Total	1,104	-

Panel C

By additional qualitative information	Frequency	Percent
Earnings Explanation	153	13.86
Internal Attribution	*102*	*66.67*
External Attribution	*79*	*51.63*
Both	*29*	*18.95*
CEO/CFO comment	280	25.36
Update	347	31.43
Total	1,104	-

Table 3: Distribution of consistency and breaks

Panel A

By consistency	Frequency	Percent
Precision	261	23.64
Disaggregation	203	18.39
Additional Info	118	10.69
Total	582	52.72
Point	14	5.36
Range	222	85.06
Open ended	0	0
Qualitative	25	9.58
Total	261	100
Earnings only	99	48.77
Revenues	72	35.47
Expenses	32	15.76
Total	203	100
CEO comment	17	14.41
Update	29	24.58
Explanation	6	5.1
None	66	55.93
Total	118	100

Panel B

By break	Frequency	Percent
Precision	160	61.3
Pos.	*5*	*3.13*
Neg.	*155*	*96.88*
Disaggregation	10	4.93
Pos.	*4*	*40.00*
Neg.	*6*	*60.00*
Additional Info	21	17.80
Pos.	*14*	*66.67*
Neg.	*7*	*33.33*

Table 4: Distribution of positive and negative keywords and total word count

Panel A

	Total		2004		2005		2006	
Keywords	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Word Count	881.35	378	1228.65	1125	789.50	447	740.89	285
Positive Keywords	15.04	3	13.50	12	15.79	9	13.40	5
Negative Keywords	6.15	1	7.62	6.50	5.42	3	4.79	2
	2007		**2008**		**2009**		**2010**	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Word Count	753.89	196	873.02	281	1761.81	616	1446.07	553.50
Positive Keywords	12.16	4	14.24	4	24.46	8	24.83	14
Negative Keywords	4.44	1	6.51	4	15.36	7	10.80	7

Panel B

	Cons_prec		Cons_disag		Cons_add		Cons_point	
Keywords	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Word Count	1241.63	492	1148.27	449	1156.85	447	751	535
Positive Keywords	19.94	11	17.56	10	17.79	9	16.83	14
Negative Keywords	8.14	4	7.55	3	7.34	3	5.26	3
	Cons_range		**Cons_qual**		**Cons_earn_only**		**Cons_revenue**	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Word Count	1084.31	424	1545.61	1189	871.02	402	746.69	363.50
Positive Keywords	17.72	8	12.12	12	13.99	8	11.96	6.50
Negative Keywords	7.48	4	8.97	10	6.39	3	5.19	2
	Cons_expense		**Cons_CEO comm**		**Cons_update**		**Cons_explan**	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Word Count	2909.53	3613	1612.48	892	1190.18	819	2113.33	1949
Positive Keywords	41.19	44	39.57	24	20.64	12	10.83	7
Negative Keywords	16.41	13	12.14	10	8.30	5	8.17	6

Table 5: Descriptive Statistics

Variable Name	N.	Mean	SD	Min	0.25	Median	0.75	Max
MISS_POST	1104	0.25	0.43	0.00	0.00	0.00	0.00	1.00
TONE	1104	0.41	0.50	-1.00	0.12	0.50	0.78	1.00
WC	1104	881.35	1244.57	30	200	378	794	9807
MEET	1104	0.75	0.43	0.00	0.00	1.00	1.00	1.00
ROA	1104	0.05	0.11	-0.54	0.03	0.06	0.10	0.30
EARN_DIFF	1104	-59.55	143.37	-454.00	-78.01	-13.20	9.30	100.84
SIZE	1104	7.59	1.84	-2.42	6.33	7.67	8.89	11.51
LEV	1104	0.17	0.15	0.00	0.03	0.15	0.27	0.72
INDUSTRY	1104	26.48	14.09	1.00	13.00	31.00	41.00	48.00

Table 6: Pearson Correlations between the variables

Panel A

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	Code_prec_time0	1																							
2	Code_disag_time0	0.0191	1																						
3	Code_add_time0	-0.1190*	-0.023	1																					
4	Cons_prec	-0.0199	0.0692*	-0.0584	1																				
5	Cons_ disag	-0.0232	0.0567	-0.0847*	0.7485*	1																			
6	Cons_ add	0.0567	0.0309	0.0733*	0.5458*	0.4488*	1																		
7	Break_prec_pos	-0.1005*	0.0254	-0.0175	0.7399*	0.5884*	0.3739*	1																	
8	Break_prec_pos	0.1288*	0.0857*	-0.0274	0.1212*	0.0725*	0.0640*	0.1638*	1																
9	Break_prec_neg	-0.1268*	0.0092	-0.0124	0.7263*	0.5822*	0.3665*	0.9817*	-0.0273	1															
10	Break_ disag	0.0172	-0.0086	0.0377	0.1493*	0.2014*	0.0598*	-0.0394	-0.0064	-0.0386	1														
11	Break_ disag _pos	0.0068	0.0151	-0.002	0.1084*	0.1270*	0.0767*	-0.0248	-0.0041	-0.0244	0.6307*	1													
12	Break_ disag _neg	0.0166	-0.0234	0.0502	0.1039*	0.1557*	0.0143	-0.0304	-0.005	-0.0299	0.7732*	-0.0045	1												
13	Break_ add	0.0400	0.0364	0.0327	0.2190*	0.1222*	0.4025*	-0.0197	0.1881*	-0.0563	0.0567	0.1020*	-0.0103	1											
14	Break_ add _pos	0.0398	0.0165	0.0785*	0.1656*	0.1134*	0.3276*	-0.0007	0.2335*	-0.0458	0.0746*	0.1279*	-0.0084	0.8139*	1										
15	Break_ add _neg	0.0128	0.0394	-0.0544	0.1436*	0.0505	0.2309*	-0.0329	-0.0054	-0.0323	-0.0076	-0.0048	-0.0059	0.5737*	-0.0091	1									
16	Cons_point	-0.1756*	-0.0464	0.0050	0.2037*	0.1761*	0.0656*	0.2063*	-0.0076	0.2105*	0.0746*	0.1279*	-0.0084	0.0435	0.0595*	-0.0091	1								
17	Cons_ range	-0.1100*	0.0826*	-0.0392	0.9016*	0.6603*	0.4482*	0.7243*	-0.0002	0.7340*	0.0952*	0.0450	0.0859*	0.1618*	0.1047*	0.1308*	-0.0569	1							
18	Cons_ qualit	0.3716*	0.0099	-0.0651*	0.2736*	0.2264*	0.3021*	0.0065	0.3524*	-0.0615*	0.1140*	0.0922*	0.0716*	0.1571*	0.1460*	0.0645*	-0.0173	-0.0764*	1						
19	Cons_earn_only	0.0021	0.2117*	-0.0553	0.1372*	0.2474*	0.1101*	0.0927*	0.0082	0.0924*	0.0380	0.0988*	-0.0318	0.0133	0.0406	-0.0343	-0.0264	0.1210*	0.0857*	1					
20	Cons_ revenue	-0.0823*	-0.1264*	0.0012	0.4402*	0.5565*	0.2411*	0.4227*	-0.0178	0.4318*	0.0909*	0.0451	0.0803*	0.0438	0.0684*	-0.0211	0.2979*	0.3709*	0.0338	-0.1135*	1				
21	Cons_ expenses	-0.002	0.0537	-0.0402	0.2597*	0.3640*	0.1325*	0.1283*	0.0688*	0.1167*	0.2114*	-0.0104	0.2810*	0.0155	0.0287	-0.0138	-0.0196	0.2501*	0.0826*	-0.0742*	-0.0456	1			
22	Cons_ update	0.0676*	0.009	-0.0980*	0.3029*	0.2874*	0.5074*	0.2148*	-0.0118	0.2200*	0.0394	0.0779*	-0.013	0.0534	-0.0199	0.1200*	0.0276	0.2172*	0.2593*	0.1593*	0.0829*	0.0331	1		
23	Cons_ceo_comm	-0.0305	0.0815*	-0.0452	0.2190*	0.1393*	0.4025*	0.0745*	-0.0094	0.0773*	0.0567	-0.0084	0.0799*	0.3204*	0.1027*	0.4066*	0.0435	0.2279*	-0.0212	0.0133	0.0438	0.0550	0.2092*	1	
24	Cons_ explanation	0.1149*	-0.0593*	-0.1208*	0.1329*	0.1239*	0.2137*	0.0046	-0.005	0.0056	-0.0071	-0.0045	-0.0055	0.0799*	-0.0084	0.1493*	-0.0084	0.0244	0.3200*	-0.0318	0.0803*	0.1341*	0.0594*	0.1701*	1

Panel B

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
1	miss_post	1																																
2	Code_prec_time0	0.0715*	1																															
3	Code_disag_time0	0.0783*	0.0191	1																														
4	Code_add_time0	-0.0517	-0.1190*	-0.023	1																													
5	Cons_prec	0.0246	-0.0199	0.0692*	-0.0584	1																												
6	Cons_ disag	0.0510	-0.0232	0.0567	-0.0847*	0.7485*	1																											
7	Cons_ add	0.0041	0.0567	0.0309	0.0733*	0.5458*	0.4488*	1																										
8	Break_prec_pos	-0.0229	-0.1005*	0.0254	-0.0175	0.7399*	0.5884*	0.3739*	1																									
9	Break_prec_pos	0.0235	0.1288*	0.0857*	-0.0274	0.1212*	0.0725*	0.0640*	0.1638*	1																								
10	Break_prec_neg	-0.0278	-0.1268*	0.0092	-0.0124	0.7263*	0.5822*	0.3665*	0.9817*	-0.0273	1																							
11	Break_ disag	-0.0109	0.0172	-0.0086	0.0377	0.1493*	0.2014*	0.0598*	-0.0394	-0.0064	-0.0386	1																						
12	Break_ disag _pos	0.0001	0.0068	0.0151	-0.002	0.1084*	0.1270*	0.0767*	-0.0248	-0.0041	-0.0244	0.6307*	1																					
13	Break_ disag _neg	-0.0141	0.0166	-0.0234	0.0502	0.1039*	0.1557*	0.0143	-0.0304	-0.005	-0.0299	0.7732*	-0.0045	1																				
14	Break_ add	-0.0189	0.0400	0.0364	0.0327	0.2190*	0.1222*	0.4025*	-0.0197	0.1881*	-0.0563	0.0567	0.1020*	-0.0103	1																			
15	Break_ add _pos	0.0096	0.0398	0.0165	0.0785*	0.1656*	0.1134*	0.3276*	-0.0007	0.2335*	-0.0458	0.0746*	0.1279*	-0.0084	0.8139*	1																		
16	Break_ add _neg	-0.0460	0.0128	0.0394	-0.0544	0.1436*	0.0505	0.2309*	-0.0329	-0.0054	-0.0323	-0.0076	-0.0048	-0.0059	0.5737*	-0.0091	1																	
17	Cons_point	-0.0091	-0.1756*	-0.0464	0.005	0.2037*	0.1761*	0.0656*	0.2063*	-0.0076	0.2105*	0.0746*	0.1279*	-0.0084	0.0435	0.0595*	-0.0091	1																
18	Cons_ range	-0.0172	-0.1100*	0.0826*	-0.0392	0.9016*	0.6603*	0.4482*	0.7243*	-0.0002	0.7340*	0.0952*	0.045	0.0859*	0.1618*	0.1047*	0.1308*	-0.0569	1															
19	Cons_ qualit	0.1235*	0.3716*	0.0099	-0.0651*	0.2736*	0.2264*	0.3021*	0.0065	0.3524*	-0.0615*	0.1140*	0.0922*	0.0716*	0.1571*	0.1460*	0.0645*	-0.0173	-0.0764*	1														
20	Cons_earn_only	-0.0164	0.0021	0.2117*	-0.0553	0.1372*	0.2474*	0.1101*	0.0927*	0.0082	0.0924*	0.0380	0.0988*	-0.0318	0.0133	0.0406	-0.0343	-0.0264	0.1210*	0.0857*	1													
21	Cons_ revenue	0.0006	-0.0823*	-0.1264*	0.0012	0.4402*	0.5565*	0.2411*	0.4227*	-0.0178	0.4318*	0.0909*	0.0451	0.0803*	0.0438	0.0684*	-0.0211	0.2979*	0.3709*	0.0338	-0.1135*	1												
22	Cons_ expenses	0.1252*	-0.002	0.0537	-0.0402	0.2597*	0.3640*	0.1325*	0.1283*	0.0688*	0.1167*	0.2114*	-0.0104	0.2810*	0.0155	0.0287	-0.0138	-0.0196	0.2501*	0.0826*	-0.0742*	-0.0456	1											
23	Cons_ update	0.0096	0.0676*	0.009	-0.0980*	0.3029*	0.2874*	0.5074*	0.2148*	-0.0118	0.2200*	0.0394	0.0779*	-0.013	0.0534	-0.0199	0.1200*	0.0276	0.2172*	0.2593*	0.1593*	0.0829*	0.0331	1										
24	Cons_ceo_comm	-0.0495	-0.0305	0.0815*	-0.0452	0.2190*	0.1393*	0.4025*	0.0745*	-0.0094	0.0773*	0.0567	-0.0084	0.0799*	0.3204*	0.1027*	0.4066*	0.0435	0.2279*	-0.0212	0.0133	0.0438	0.055	0.2092*	1									
25	Cons_ explanation	0.0429	0.1149*	-0.0593*	-0.1208*	0.1329*	0.1239*	0.2137*	0.0046	-0.005	0.0056	-0.0071	-0.0045	-0.0055	0.0799*	-0.0084	0.1493*	-0.0084	0.0244	0.3200*	-0.0318	0.0803*	0.1341*	0.0594*	0.1701*	1								
26	TONE_H	-0.0950*	-0.0435	-0.0777*	0.0257	0.0114	-0.0062	0.0132	0.0218	-0.0049	0.023	0.0290	-0.0222	0.0555	0.0297	0.0441	-0.0111	0.0397	0.0177	-0.0449	-0.0748*	0.022	0.0021	-0.0215	-0.0029	-0.0274	1							
27	wc	0.0715*	0.0478	-0.0299	-0.1682*	0.1611*	0.1018*	0.0766*	0.0630*	0.0456	0.055	0.0724*	0.0466	0.0553	0.0751*	0.0435	0.0679*	0.0105	0.1357*	0.0866*	-0.0236	-0.0286	0.2817*	0.0436	0.0818*	0.0732*	-0.0044	1						
28	meet	-0.1470*	-0.1165*	-0.0335	-0.0151	-0.0247	-0.0199	-0.0417	-0.0211	-0.0849*	-0.005	0.0116	0.0004	0.0146	-0.0106	0.0100	-0.0323	0.0473	0.0005	-0.1076*	0.0314	-0.0574	0.0011	-0.0448	-0.0411	-0.0137	0.0533	-0.0534	1					
29	ROA	-0.1648*	-0.1438*	-0.0297	0.0299	0.0329	0.0533	0.0193	0.0255	-0.003	0.0264	0.0337	0.0303	0.0187	0.0415	0.0344	0.0229	0.0076	0.0657*	-0.0887*	0.0480	0.0581	-0.0731*	0.0567	0.0175	-0.2091*	0.1371*	-0.0770*	0.1858*	1				
30	earn_diff	0.0732*	-0.0012	-0.0509	0.1075*	0.0067	-0.0002	0.0144	0.0097	-0.0843*	0.0261	-0.0719*	0.0163	-0.1059*	-0.0678*	-0.0517	-0.0438	-0.0229	0.0217	-0.022	-0.025	0.0393	-0.0623*	-0.0082	-0.0291	0.0632*	-0.1846*	-0.0720*	-0.1177*	-0.2120*	1			
31	size	-0.1335*	-0.0834*	0.1477*	-0.1449*	0.1286*	0.0985*	0.0876*	0.0886*	0.0335	0.0833*	0.0162	-0.002	0.0224	0.0670*	0.041	0.0575	-0.0331	0.1623*	-0.0451	0.2206*	-0.0568	0.0513	0.0854*	0.0617*	-0.0036	-0.0079	0.0389	0.1500*	0.2459*	-0.3757*	1		
32	leverage	0.0744*	0.0364	0.0084	0.0009	0.0005	0.0044	-0.0134	0.0119	-0.0039	0.0128	-0.0584	-0.0454	-0.0381	-0.0262	-0.0154	-0.0234	-0.0232	-0.0019	0.0241	0.0342	-0.0417	0.0806*	-0.0095	-0.0438	0.0841*	-0.0622*	0.0383	-0.0148	-0.1735*	0.0668*	0.1246*	1	
33	indsustry	0.0536	0.0193	0.0034	0.0323	-0.1076*	-0.0443	-0.0479	-0.0486	0.0025	-0.0498	-0.0515	0.0258	-0.0874*	-0.0189	-0.0165	-0.0092	0.0185	-0.1351*	0.0428	0.0266	-0.0101	-0.1658*	0.0004	-0.0457	-0.0025	-0.1093*	-0.1214*	-0.0722*	-0.0442	0.1130*	-0.0029	-0.0950*	1

Table 7

	Dependent Variable = Miss_post			
	Model 1	*Model 2*	*Model 3*	*Model 4*
CODE_PREC_T0	0.066	0.058	0.081	0.046
	(0.69)	(0.60)	(0.84)	(0.46)
CONS_PREC	0.614**	0.616**		0.645**
	(2.56)	(2.56)		(2.65)
BREAK_PREC	-0.614**			
	(2.06)			
BREAK_PREC_POS		-0.081		-0.114
		(0.08)		(0.11)
BREAK_PREC_NEG		-0.638**		-0.588*
		(2.12)		(1.93)
TONE			-0.363**	-0.359**
			(2.48)	(2.44)
MEET	-0.533***	0.526***	-0.533***	-0.519***
	(3.33)	(3.28)	(3.30)	(3.18)
ROA	-2.301***	-2.302***	-2.431***	-2.483***
	(3.15)	(3.15)	(3.23)	(3.25)
EARN_DIFF	-0.000	-0.000	-0.000	-0.000
	(0.14)	(0.08)	(0.50)	(0.62)
SIZE	-0.132***	-0.132***	-0.143***	-0.158***
	(2.95)	(2.96)	(3.15)	(3.43)
LEV	1.026**	1.029**	1.044**	1.102**
	(2.18)	(2.18)	(2.16)	(2.27)
INDUSTRY	0.010*	1.010*	0.008	0.009*
	(1.89)	(1.89)	(1.40)	(1.68)
INTERCEPT	-0.301	-0.284	0.023	0.067
	(0.70)	(0.66)	(0.05)	(0.15)
Pseudo R-squared	0.054	0.054	0.059	0.064
No. of Obs	1,099	1,099	1,077	1,077
LR Chi-sq	66.30	66.60	70.92	77.80
	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000

Table 8

	Dependent Variable = Miss_post			
	Model 1	*Model 2*	*Model 3*	*Model 4*
CODE_DISAG_T0	0.193***	0.193***	0.206***	0.203***
	(2.77)	(2.76)	(2.91)	(2.85)
CONS_ DISAG	0.407**	0.407**		0.423**
	(2.22)	(2.22)		(2.28)
BREAK_ DISAG	-0.288			
	(0.35)			
BREAK_ DISAG _POS		-0.189		-0.228
		(0.16)		(0.19)
BREAK_ DISAG _NEG		-0.371		-0.296
		(0.33)		(0.26)
TONE			-0.328**	-0.329**
			(2.23)	(2.23)
MEET	-0.515***	-0.514***	-0.520***	-0.506***
	(3.22)	(3.21)	(3.21)	(3.11)
ROA	-2.370***	-2.372***	-2.532***	-2.595***
	(3.28)	(3.28)	(3.39)	(3.45)
EARN_DIFF	-0.000	-0.000	-0.000	-0.000
	(0.13)	(0.14)	(0.49)	(0.61)
SIZE	-0.154***	-0.154***	-0.168***	-0.18***
	(3.37)	(3.37)	(3.62)	(3.82)
LEV	1.023**	1.023**	1.088**	1.101**
	(2.16)	(2.16)	(2.25)	(2.26)
INDUSTRY	0.010*	0.010*	0.008	0.009
	(1.78)	(1.77)	(1.45)	(1.56)
INTERCEPT	-0.680*	-0.679*	-0.374	-0.389
	(1.66)	(1.66)	(0.87)	(0.91)
Pseudo R-squared	0.058	0.058	0.065	0.069
No. of Obs	1,099	1,099	1,077	1,077
LR Chi-sq	71.66	71.67	78.60	83.68
	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000

Table 9

	Dependent Variable = Miss_post			
	Model 1	*Model 2*	*Model 3*	*Model 4*
CODE_ADD_T0	-0.083**	-0.089**	-0.080**	-0.089**
	(2.17)	(2.31)	(2.07)	(2.27)
CONS_ ADD	0.183	0.184		0.213
	(0.72)	(0.73)		(0.83)
BREAK_ ADD	-0.265			
	(0.43)			
BREAK_ ADD _POS		0.372		0.418
		(0.57)		(0.63)
BREAK_ ADD _NEG		Omitted		omitted
		Omitted		omitted
TONE			-0.360**	-0.366**
			(2.45)	(2.49)
MEET	-0.550***	-0.562***	-0.549***	-0.555***
	(3.45)	(3.52)	(3.40)	(3.42)
ROA	-2.216***	-2.22***	-2.403***	-2.400***
	(3.05)	(3.06)	(3.19)	(3.17)
EARN_DIFF	0.000	0.000	-0.000	-0.000
	(0.01)	(0.00)	(0.41)	(0.49)
SIZE	-0.137***	-0.135***	-0.158***	-0.159***
	(3.07)	(3.02)	(3.45)	(3.46)
LEV	1.023**	1.02**	1.087**	1.097**
	(2.17)	(2.16)	(2.24)	(2.25)
INDUSTRY	0.009*	0.009*	0.008	0.008
	(1.75)	(1.75)	(1.48)	(1.51)
INTERCEPT	0.505	0.540	0.818*	0.864*
	(1.11)	(1.19)	(1.74)	(1.83)
Pseudo R-squared	0.052	0.052	0.062	0.062
No. of Obs	1,099	1,099	1,077	1,077
LR Chi-sq	63.93	64.36	74.42	75.70
	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000

Table 10

	Dependent Variable = Miss_post		
	Model 5	*Model 6*	*Model 7*
CONS_POINT	-1.590*	-1.417*	-1.476*
	(1.93)	(1.66)	(1.69)
CONS_ RANGE	-1.214**	-1.012*	-1.095**
	(2.45)	(1.95)	(2.04)
TONE		-0.647*	-0.623*
		(1.87)	(1.76)
WC			0.003**
			(2.64)
MEET	-0.149	-0.201	-0.065
	(0.43)	(0.56)	(0.18)
ROA	-2.241	-4.464*	-4.110
	(1.19)	(1.83)	(1.59)
EARN_DIFF	-0.000	-0.001	-0.000
	(0.05)	(0.80)	(0.51)
SIZE	-0.249***	-0.311***	-0.298***
	(2.58)	(3.04)	(2.95)
LEV	1.698	1.550	1.285
	(1.53)	(1.28)	(1.04)
INDUSTRY	0.001	-0.004	-0.001
	(0.08)	(0.40)	(0.10)
INTERCEPT	1.939**	2.817***	2.224**
	(2.21)	(2.94)	(2.27)
Pseudo R-squared	0.102	0.134	0.157
No. of Obs	261	257	257
LR Chi-sq	31.02	40.43	47.25
	p = 0.0000	p = 0.0000	p = 0.0000

Table 11

	Dependent Variable = Miss_post		
	Model 5	*Model 6*	*Model 7*
CONS_EARN_ONLY	-0.485	-0.502	-0.364
	(1.15)	(1.17)	(0.82)
CONS_ REVENUE	-1.259**	-1.228**	-0.967*
	(2.69)	(2.59)	(1.92)
TONE		-0.531	-0.530
		(1.45)	(1.43)
WC			0.002*
			(1.62)
MEET	-0.309	-0.275	-0.160
	(0.82)	(0.72)	(0.41)
ROA	-5.371*	-5.175*	-5.025*
	(1.92)	(1.81)	(1.69)
EARN_DIFF	0.000	-0.000	-0.000
	(0.10)	(0.27)	(0.17)
SIZE	-0.469***	-0.480***	-0.437***
	(3.91)	(3.91)	(3.52)
LEV	-1.024	-0.854	-0.949
	(0.74)	(0.60)	(0.66)
INDUSTRY	-0.004	-0.006	-0.003
	(0.36)	(0.50)	(0.29)
INTERCEPT	4.223***	4.469***	3.606**
	(3.63)	(3.74)	(2.78)
Pseudo R-squared	0.136	0.146	0.156
No. of Obs	202	202	202
LR Chi-sq	33.45	35.80	38.37
	p = 0.0001	p = 0.0000	p = 0.0000

Table 12

	Dependent Variable = Miss_post		
	Model 5	*Model 6*	*Model 7*
CONS_CEO_COMM	-2.436**	-2.508**	-2.530**
	(2.00)	(2.04)	(2.01)
CONS_ UPDATE	0.575	0.486	0.472
	(0.92)	(0.74)	(0.70)
TONE		-0.120	-0.120
		(0.20)	(0.20)
WC			0.000*
			(0.09)
MEET	-1.126*	-1.146*	-1.140*
	(1.79)	(1.79)	(1.77)
ROA	-8.852*	-8.670*	-8.619*
	(1.81)	(1.68)	(1.66)
EARN_DIFF	-0.005*	-0.005*	-0.005*
	(1.76)	(1.89)	(1.88)
SIZE	-0.734***	-0.808***	-0.805***
	(3.59)	(3.59)	(3.54)
LEV	1.544	3.281	3.235
	(0.74)	(1.38)	(1.33)
INDUSTRY	0.033*	0.033*	0.033*
	(1.66)	(1.64)	(1.64)
INTERCEPT	4.472***	4.831***	4.787**
	(2.62)	(2.71)	(2.59)
Pseudo R-squared	0.343	0.362	0.362
No. of Obs	118	118	118
LR Chi-sq	45.92	48.26	48.27
	p = 0.0000	p = 0.0000	p = 0.0000

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