Analysts' long-term growth forecasts and the post-earnings-announcement drift

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Received 27 May 2022
Revised 27 July 2022
Accepted 28 July 2022

Abstract

Purpose – This study examines the relation between the presence of analysts' long-term growth (LTG) forecasts and the post-earnings-announcement drift (PEAD).

Design/methodology/approach – Using a sample of firm-quarters from 1995 to 2013, the author conducts various regression analyses.

Findings – The author finds that the magnitude of PEAD is significantly smaller for firms with LTG forecasts. The relationship holds after controlling for a wide range of explanatory variables for PEAD returns or for the presence of LTG forecasts. The author further investigates three nonexclusive hypotheses to explain this relationship. First, LTG forecasts may convey incremental value-relevant information that facilitates investors' processing of short-term earnings information. Second, the presence of LTG forecasts may indicate superiority in analysts' short-term forecast ability and identify firms with more efficient short-term forecasts. Third, the presence of LTG forecasts may be associated with cross-sectional differences in the persistence of earnings surprises. The author finds that none of these fully accounts for the negative relationship between the presence of LTG forecasts and PEAD returns. Instead, the relationship may be a result of the presence of LTG forecasts capturing some unobservable firm characteristics beyond those identified in prior studies.

Originality/value – This study contributes to the PEAD literature by identifying a novel analyst-based predictor of the cross-sectional variation in PEAD returns.

Keywords Analysts' long-term growth forecasts, Post-earnings-announcement drift, Anomaly

Paper type Research paper

1. Introduction

Post-earnings-announcement drift (PEAD) is the tendency for stock prices to drift in the direction of earnings surprises in the months following quarterly earnings announcements (Ball & Brown, 1968; Bernard & Thomas, 1989, 1990). The phenomenon was first documented by Ball and Brown (1968) and is one of the most compelling challenges to the efficient market hypothesis (Fama, 1998; Hung, Li, & Wang, 2015). Numerous studies have proposed explanations for PEAD (Barberis, Shleifer, & Vishny, 1998; Bernard & Thomas, 1990; Chordia & Shivakumar, 2005; Hirshleifer, Lim, & Teoh, 2009; Kovacs, 2016), and some studies also document variables that predict cross-sectional variations in PEAD returns (Rangan & Sloan, 1998; Narayanamoorthy, 2006; Bartov, Radhakrishnan, & Krinsky, 2000).

Recognizing the important roles financial analysts play in the financial market, a number of studies investigate the relation between analysts' forecasts and PEAD (Abarbanell &

The author thanks Louis K.C. Chan, Laura Yue Li, Gans Narayanamoorthy, Theodore Sougiannis, Michael Minye Tang and Wei Zhu for their insightful feedback and advice on an earlier draft of this paper.

Data: Data are available from public sources identified in the text.

China Accounting and Finance Review
Vol. 25 No. 3, 2023
pp. 313-337
Emerald Publishing Limited
e-ISSN: 2307-3055
p-ISSN: 1029-807X
DOI 10.1108/CAFR-05-2022-0059

Bernard, 1992; Zhang, 2008). These studies find that PEAD is closely related to analysts' forecasts. For example, Abarbanell and Bernard (1992) show that analysts' short-term forecasts display the same form of underreaction to earnings information as exhibited by PEAD, and they suggest that investors' fixation on inefficient analysts' forecasts may partially explain PEAD. Zhang (2008) finds that the immediate stock market response to earnings information is larger, and that the drift is smaller, for firms with responsive analysts' short-term forecast revisions. She interprets her results as suggesting that analysts' short-term forecast responsiveness facilitates market efficiency and mitigates PEAD.

In this study, I explore the relation between the presence of analysts' long-term growth (LTG) forecasts and PEAD. LTG forecasts are one of the most common voluntary activities of financial analysts. For example, in 2009, around two-thirds of the analyst-followed firms have LTG forecasts, and around half of the financial analysts issue LTG forecasts. Despite the widespread availability of LTG forecasts, it is not clear what roles these forecasts play in financial markets. Most prior literature describes LTG forecasts as providing little incremental information (Chan, Karceski & Lakonishok, 2003). However, the fact that analysts keep issuing LTG forecasts suggests that there is demand for such forecasts. In fact, several studies show that LTG forecasts are used by investors and analysts themselves in valuing firms (Copeland, Dolgoff, & Moel, 2004; Bradshaw, 2004). Furthermore, a recent study by Jung, Shane and Yang (2012) finds that stock recommendations accompanied by LTG forecasts are more value-relevant, and analysts who publish these forecasts have better career outcomes. The authors interpret these findings to suggest that LTG forecasts provide investors with valuable information about firms' long-term prospects and that the publication of these forecasts plays an important role in promoting market price discovery.

I hypothesize in this study that the presence of LTG forecasts may associate with the cross-sectional variations in PEAD returns through three channels. First, LTG forecasts may convey value-relevant information that facilitates investors' processing of earnings information and thus directly mitigate PEAD (*forecast informativeness hypothesis*). Specifically, LTG forecasts include two types of information that is relevant for PEAD: short-term earnings related information and industry-wide information. LTG forecasts are forecasts for firm earnings from the current year till three to five years into the future. By definition, LTG forecasts contain short-term earnings forecasts. In addition, since analysts take a long-term perspective when making LTG forecasts, short-term transitory fluctuations in earnings are less relevant for these forecasts. As a result, these forecasts are more likely to capture the long-term persistent part of short-term earnings. This incremental information about short-term earnings may play a role in improving investors' understanding of the implications of earnings information by enabling them to understand and use analysts' short-term forecasts better. In addition, LTG forecasts may also convey industry-related information. Mean reversion of firm earnings (Fama & French, 2000; Fairfield, Ramnath, & Yohn, 2009) implies that LTG forecasts must rely greatly on analysts' understanding of the industry and macroeconomic conditions. Studies show that investors' underreaction to industry-wide earnings news contributes to the drifts following analyst forecast revisions (Hui & Yeung, 2013) and earnings announcements (Kovacs, 2016). LTG forecasts may alleviate such underreaction (and thus mitigate PEAD) by facilitating investors' understanding of the industry-related information.

Second, the presence of LTG forecasts may indicate superiority in analysts' short-term forecast ability (*analyst ability hypothesis*). Long-term forecasting is considered in practice as highly difficult (Chan, Karceski, & Lahonishok, 2003; Dichev, Graham, Harvey, & Rajgopal, 2013). Thus, only analysts with superior forecast ability may be able to provide LTG forecasts. In addition, due to the information asymmetry between analysts and investors, capable analysts may intentionally use the issuance of LTG forecasts to show their forecast ability. Consequently, the presence of LTG forecasts may be informative about the efficiency of analysts' short-term forecasts. Prior studies suggest that the efficiency of analysts' short-term forecasts relate to PEAD (Zhang, 2008; Abarbanell & Bernard, 1992). Specifically, Abarbanell and Bernard (1992) suggest that investors' fixation on inefficient analysts' forecasts causes PEAD. Zhang (2008) argues that analysts' timely revisions of their short-term forecasts mitigate PEAD. Thus, the presence of LTG forecasts may be associated with lower PEAD returns if it identifies firms with higher analysts' short-term forecast efficiency.

Third, the presence of LTG forecasts may associate with firms' time-series properties of earnings (*earnings persistence hypothesis*). For example, the persistence of standardized unexpected earnings (SUE) is likely to be low when there is high information uncertainty, while analysts are less likely to issue LTG forecasts under this situation due to increased information processing costs in a highly uncertain information environment. This leads to a positive association between the presence of LTG forecasts and SUE persistence. Prior studies suggest that investors' insufficient understanding of the cross-sectional differences in SUE persistence results in predictable cross-sectional variations in PEAD returns (Rangan & Sloan, 1998; Narayanamoorthy, 2006; Cao & Narayanamoorthy, 2012). To the extent that the presence of LTG forecasts is associated with lower SUE persistence and that investors fail to understand this relation, I anticipate lower PEAD returns for firms with LTG forecasts.

My empirical analyses start with an examination of the association between the *ex ante* presence of LTG forecasts and PEAD returns. Using a sample of firm-quarters during 1995–2013 with analysts' short-term forecasts, I find that the magnitude of PEAD is significantly smaller for firms that also have LTG forecasts. While the average spread in abnormal returns between top and bottom SUE deciles is 6.7% per quarter for firms without LTG forecasts, it is 2.2% per quarter for firms with LTG forecasts. This return difference remains statistically significant after controlling for a wide range of explanatory variables used in prior research to explain the cross-sectional variations in PEAD returns.

I further assess each of the three nonmutually exclusive hypotheses about the sources of this return predictability. First, if the relationship between the presence of LTG forecasts and PEAD returns is due to LTG forecasts conveying value-relevant information which facilitates market efficiency (*forecast informativeness hypothesis*), we would expect that the timing of LTG forecast revisions matters. In other words, even if a firm has LTG forecasts, if analysts do not revise these forecasts in a timely manner after earnings announcements, we would not expect that these forecasts play a role in mitigating PEAD. I find that for a sample of firms with responsive analysts' short-term forecast revisions, the responsiveness of LTG forecast revisions does not have any effect on PEAD returns beyond the effect of firm size. This is inconsistent with the forecast informativeness hypothesis as an explanation for the negative relationship between the presence of LTG forecasts and PEAD returns.

Second, if the relationship between the presence of LTG forecasts and PEAD returns is due to the presence of LTG forecasts indicating superior analysts' short-term forecast ability (*analyst ability hypothesis*), we would expect that there is a positive association between the presence of LTG forecasts and analysts' short-term forecast efficiency. With respect to this prediction, I find mixed evidence. Results show that the presence of LTG forecasts is associated with more responsive analysts' short-term forecast revisions, but it is not associated with the correlation between analysts' short-term forecast errors and SUE [1]. If the relationship between the presence of LTG forecasts and PEAD returns is solely driven by its predictive power for future analysts' short-term forecast responsiveness, the relationship should not be significant after this responsiveness is controlled for. However, the effect of LTG forecasts on PEAD returns remains statistically significant, and only goes slightly from −0.038 to −0.033, after controlling for the responsiveness of analysts' short-term forecasts. Thus, I interpret the results as being inconsistent with the analyst ability hypothesis as an explanation for the negative relationship between the presence of LTG forecasts and PEAD returns.

Third, if the relationship between the presence of LTG forecasts and PEAD returns is due to the association between the presence of LTG forecasts and the time-series properties of earnings (*earnings persistence hypothesis*), we would expect that there is a negative association between the presence of LTG forecasts and SUE persistence. However, I find that SUE persistence is not lower, but higher, for firms with LTG forecasts. Further analysis using Mishkin (1983) tests reinforces this finding. The results suggest that the negative relationship between the presence of LTG forecasts and PEAD returns is not driven by investors' underestimation of the effect of LTG forecasts on SUE persistence (i.e. earnings persistence hypothesis), but is likely a result of higher price efficiency associated with firms with LTG forecasts.

Lastly, I control for a basket of firm-level determinants of LTG forecasts which may have confounding effects on the presence of LTG forecasts and PEAD returns. Some of these firm-level determinants of LTG forecasts were not examined in prior studies. Specifically, I find that firm-quarters are more likely to have LTG forecasts when earnings volatility and R&D intensity are lower, when trading volume is higher, when the firm has recently been through a restructuring or when the earnings announcements are for the fourth fiscal quarter. Nevertheless, controlling for these LTG forecast determinants does not change the results. Overall, my findings suggest that the negative relationship between the presence of LTG forecasts and PEAD returns is not due to any of the three explanations hypothesized, and thus I conjecture that it may be a result of the presence of LTG forecasts capturing some unobservable firm characteristics beyond those identified in prior studies.

This study makes several important contributions. First, it extends the literature on PEAD. The extant studies have long been interested in identifying variables that predict the cross-sectional variations in PEAD returns (Rangan & Sloan, 1998; Narayanamoorthy, 2006; Bartov, Radhakrishnan, & Krinsky, 2000). While several studies document a close relation between analysts' forecasts and PEAD (Abarbanell & Bernard, 1992; Zhang, 2008), this is the first one that investigates the relationship between the presence of LTG forecasts and PEAD.

Second, this study also extends studies on LTG forecasts. I explore the uses of LTG forecasts from two new perspectives: (1) whether these forecasts play a direct role in facilitating market efficiency and (2) whether the presence of these forecasts captures information about analysts' ability and firms' fundamental earnings process. The findings from this study advance our understanding of LTG forecasts by (1) ruling out the direct role of these forecasts in mitigating PEAD and (2) showing that the presence of LTG forecasts is an indicator of analysts' short-term forecast responsiveness, as well as SUE persistence.

Finally, the findings from this study are relevant to investors. For investors who trade on the drift following earnings announcements, findings from this study may help them improve their trading strategy by taking into account the presence of LTG forecasts. Specifically, this study suggests that PEAD strategy earns higher returns for firms without LTG forecasts (6.7% per quarter) than for firms with LTG forecasts (2.2% per quarter). Focusing on firms without LTG forecasts increases the PEAD strategy returns by more than half from approximately 4.1% to 6.7% per quarter.

The rest of the paper proceeds as follows. Section 2 describes the data. Section 3 reports the basic characteristics of LTG forecasts. Section 4 presents the main empirical results between the presence of LTG forecasts and PEAD returns. Section 5 investigates the three hypotheses to explain the LTG forecast effect. Section 6 concludes.

2. Data

2.1 Sample selection

Data used in this study are obtained from CRSP-Compustat Merged (quarterly), CRSP (daily), I/B/E/S (summary and detail) and CDA/Spectrum databases. The sample selection procedure starts with all quarterly earnings announcements from CRSP-Compustat Merged database between 1995 and 2013. I delete observations with (1) more than one earnings announcement on the same date, (2) earnings announcement date less than 35 days or more than 150 days after the previous earnings announcement date or (3) earnings announcement date on/before or more than 95 days after the corresponding fiscal period end, as these observations are potentially subject to data errors. I restrict the sample to announcements that have stock return data in CRSP and have quarterly earnings forecasts in I/B/E/S. Institutional ownership data are obtained from CDA/Spectrum. I require that every observation has nonmissing data to calculate SUE. To avoid the possible influence of small illiquid stocks, I eliminate penny stocks (stocks with price lower than $1). My final sample consists of 9,166 firms and 219,098 firm-quarter observations from 1995 to 2013. Table 1 summarizes the sample selection procedure.

2.2 Variable definitions

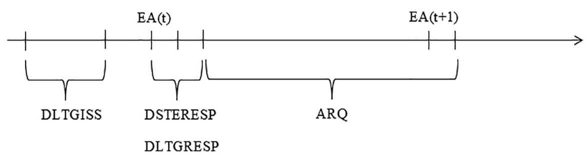
Figure 1 shows the timeline for measurement of variables. Following prior literature (Livnat & Mendenhall, 2006; Zhang, 2008, 2012), the drift window starts two trading days after quarter t earnings announcement date and ends one trading day after quarter t+1 earnings announcement date. The presence of LTG forecasts is measured in the month prior to the month of quarter t earnings announcements. Consistent with Zhang (2008), short- and long-term forecast responsiveness are measured within two trading days after quarter t earnings announcement, which are trading days 0 and 1.

My analyses focus on the effects of firm-level presence of LTG forecasts on PEAD returns. The main dependent variable of interest is abnormal returns during the quarter after earnings announcements. Following Zhang (2008), I use size-adjusted returns (ARQ) as proxy for abnormal returns and define ARQ as the difference between a firm's quarterly

All Compustat-CRSP merged database firm-quarters between 1995 and 2013	4,83,559	100%
Drop observations with more than one earnings announcement on the same date for the same firm	(1,120)	0%
Drop if current earnings announcement is less than 35 days or more than 150 days away from the previous earnings announcement	(7,929)	−2%
Drop observations whose current quarter earnings announcement date is on/before or more than 95 days after current quarter fiscal period end date	(3,323)	−1%
Drop observations that do not have quarterly earnings forecasts from I/B/E/S	(1,71,104)	−35%
Drop observations that do not have matching stock returns from CRSP	(42,132)	−9%
Drop observations with missing SUE	(34,016)	−7%
Drop penny stocks (stocks with price lower than $1)	(2,891)	−1%
Drop the first announcement if two earnings announcements occur in the same calendar quarter for the same firm	(1,946)	0%
Total	2,19,098	45%

Note(s): This table reports the sample selection procedures. Data are firm-quarter observations from 1995 to 2013

Table 1. Sample selection



Note(s): This graph illustrates the timeline for measurement of variables. See Appendix 1 for variable definitions

Figure 1. Timeline for measurement of variables

buy-and-hold returns (calculated as the compounded raw returns, starting from two days after quarter t earnings announcement through one day after quarter t+1 earnings announcement) and the same period returns for the size decile for which the firm belongs (where size deciles are determined by the total market capitalizations on the earnings announcement date).

The main independent variable of interest is the interaction between SUE and the presence of LTG forecasts (DLTGISS). Following Cao and Narayanamoorthy (2012), I define SUE as current quarter's earnings minus earnings from the corresponding quarter one year ago, scaled by the previous fiscal quarter's closing market capitalization [2]. DLTGISS is an indicator variable that equals to one if more than one analyst issues LTG forecast for the firm in the month prior to the month of quarter t earnings announcement. The definitions of variables are summarized in Appendix 1.

3. Basic characteristics of LTG forecasts

3.1 Frequency of LTG forecasts

Table 2 Panel A shows the percentage of firm-quarters which have LTG forecasts by year. On average, 59.43% of the firm-quarters have more than one analyst who issue LTG forecasts. Although the percentage of firm-quarters which have LTG forecasts has been decreasing since 2002, as of 2013, still more than one-third (39.74%) of the firms continue to have LTG forecasts.

3.2 Determinants of the firm-level presence of LTG forecasts

To better understand the properties of LTG forecasts, I examine the determinants of LTG forecasts. I follow Zhang (2008) and estimate the following logit model with standard errors clustered at the firm level:

$$\begin{aligned} Prob(\mathrm{DLTGISS}_{i,t}=1) = f(&\alpha_0+\alpha_1\mathrm{LNSIZE}_{i,t}+\alpha_2\mathrm{AGE}_{i,t}+\alpha_3\mathrm{EVOL}_{i,t}\\ &+\alpha_4\mathrm{ALTMANZ}_{i,t}+\alpha_5\mathrm{LOSS}_{i,t}+\alpha_6\mathrm{MERGE}_{i,t}\\ &+\alpha_7\mathrm{SPECIAL}_{i,t}+\alpha_8\mathrm{STENUM}_{i,t}+\alpha_9\mathrm{QTR4}_{i,t}\\ &+\alpha_{10}\mathrm{BNEWS}_{i,t}+\alpha_{11}\mathrm{BM}_{i,t}+\alpha_{12}\mathrm{DRD}_{i,t}+\alpha_{13}\mathrm{INST}_{i,t}\\ &+\alpha_{14}\mathrm{EXP}_{i,t}+\alpha_{15}\mathrm{NUMFIRM}_{i,t}+\alpha_{16}\mathrm{DCFISS}_{i,t}\\ &+\alpha_{17}\mathrm{BSIZE}_{i,t}+\alpha_{18}\mathrm{LNVOLUME}_{i,t}+\alpha_{19}\mathrm{PERCLTG}_{i,t}\\ &+\text{Year Controls}+\text{Industry Controls}+\varepsilon_{i,t}) \end{aligned} \tag{0}$$

The variables in Model 0 are discussed in Appendix 2. The model includes fixed year and industry effects to account for cross-year and cross-industry differences in the average firm-level presence of LTG forecasts. Throughout the analysis, all continuous explanatory variables are winsorized by calendar quarter at the 1st and the 99th percentile to mitigate the influence of outliers.

Table 2 Panel B reports the regression results examining the determinants of the firm-level presence of LTG forecasts. On average, larger and younger firms with less volatile earnings, higher short-term analyst following, higher institutional ownership and higher trading volumes are more likely to have LTG forecasts. These firms also tend to have higher book-to-market ratios and are less likely to have research and development (R&D) expenditures. The possibility that these firms have losses is lower, while they are more likely to have recently been through a restructuring. The analysts who cover these firms are likely to be more experienced, work for larger brokerage firms, follow a larger number of firms and more likely to issue cash flow forecasts.

Panel A: LTG forecast issuance by year			
Year	*N* (total)	*N* (DLTGISS = 1)	% (DLTGISS = 1)
1995	10,017	6,663	66.52%
1996	11,112	7,565	68.08%
1997	12,395	8,676	70.00%
1998	13,247	9,169	69.22%
1999	13,084	9,025	68.98%
2000	12,494	8,223	65.82%
2001	11,953	7,622	63.77%
2002	11,576	7,892	68.18%
2003	11,462	7,659	66.82%
2004	11,628	7,093	61.00%
2005	11,666	7,021	60.18%
2006	11,699	6,817	58.27%
2007	11,747	6,517	55.48%
2008	11,400	6,021	52.82%
2009	11,266	5,327	47.28%
2010	11,357	4,915	43.28%
2011	10,591	5,192	49.02%
2012	10,091	4,710	46.68%
2013	10,313	4,098	39.74%
Overall	2,19,098	1,30,205	59.43%

Panel B: Determinants of the firm-level presence of LTG forecasts	DLTGISS
LNSIZE	0.231***
	(8.117)
AGE	−0.011***
	(−5.982)
EVOL	−4.717***
	(−8.417)
ALTMANZ	−0.003
	(−1.143)
LOSS	−0.712***
	(−17.797)
MERGE	0.167
	(1.317)
SPECIAL	0.144***
	(4.705)
STENUM	0.308***
	(29.501)
QTR4	0.225***
	(15.670)
BNEWS	0.116***
	(5.525)
BM	0.164***
	(3.598)
DRD	−0.295***
	(−5.865)
INST	0.841***
	(8.830)
EXP	0.025**
	(2.483)
NUMFIRM	0.011***
	(3.047)
DCFISS	0.376***
	(7.469)

(*continued*)

Table 2. Basic characteristics of LTG forecasts

Panel B: Determinants of the firm-level presence of LTG forecasts	DLTGISS
BSIZE	0.003***
	(5.365)
LNVOLUME	0.125***
	(6.569)
PERCLTG	1.737***
	(26.672)
Year dummies	Included
Industry dummies	Included
Observations	150,447

Note(s): This table reports the summary statistics and regression results on the basic characteristics of LTG forecasts. See Appendix 1 for variable definitions. Panel A reports the LTG forecast issuance by year. Panel B reports the regression results examining the determinants of the firm-level presence of LTG forecasts. The model is estimated using logit regression with standard errors clustered at the firm level. Z-statistics are reported in parentheses. ***, **, * indicate significantly different from zero at the 1%, 5%, 10% level, respectively

Table 2.

4. LTG forecasts and PEAD returns

4.1 Univariate analysis

Figure 2 depicts ARQ by the magnitude of earnings surprise and whether or not the firm has LTG forecasts in the month prior to the month of earnings announcement. Firms with LTG forecasts have significantly lower PEAD returns in the quarter after earnings announcement, suggesting more efficient price reactions for firms with LTG forecasts. The pattern is present for all SUE deciles, while strongest for the most positive decile.

Table 3 reports the average size-adjusted returns for portfolios formed based on SUE deciles and the presence of LTG forecasts. SUE deciles and the presence of LTG forecasts are independently sorted. For firms with LTG forecasts, the abnormal return is only significant for the highest SUE decile, while for firms without LTG forecasts, the abnormal returns are significant for almost all SUE deciles.

To better understand the nature of the differential PEAD returns between firms with and without LTG forecasts, I examine the drift at various horizons in Figure 3. I depict the difference in the average buy-and-hold size-adjusted returns between the top and bottom SUE decile from day 2 to day t after earnings announcements (t = 10, 20, . . ., 90). Firms with LTG forecasts have lower PEAD returns over all horizons. This suggests that the pattern documented in Figure 2 is not driven by any particular return-accumulation horizon.

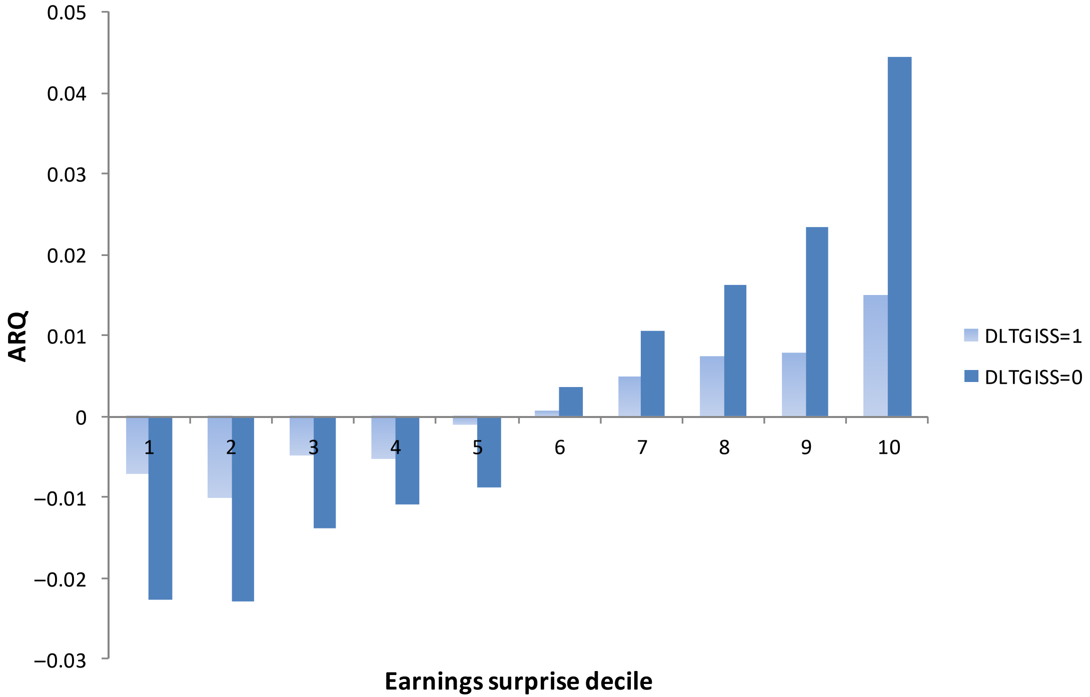
4.2 Multivariate regressions

In addition to the portfolio test, I also conduct regression analysis on the relationship between the presence of LTG forecasts and PEAD returns. One of the advantages of regression analysis is that it enables me to control for other variables that were previously shown to be associated with PEAD returns. Specifically, I estimate the following model using ordinary least squares regression with standard errors clustered at the firm level:

$$\begin{aligned}\mathrm{ARQ}_{i,t+1} = {} & \alpha_0 + \alpha_1\mathrm{PSUE}_{i,t} + \alpha_2\mathrm{DLTGISS}_{i,t} + \alpha_3\mathrm{PSUE}_{i,t} * \mathrm{DLTGISS}_{i,t} + \mathit{Controls}1_{i,t} \\ & + \mathrm{PSUE}_{i,t} * \mathrm{Controls}1_{i,t} + \mathrm{Year\ Controls} + \mathrm{Industry\ Controls} + \varepsilon_{i,t+1} \qquad (1)\end{aligned}$$

where

Controls1 = a vector of control variables that were previously identified as being associated with PEAD. These control variables are firm size (PSIZE), analyst forecast



Note(s): This figure depicts ARQ by the magnitude of earnings surprise and whether or not the firm has LTG forecasts in the month prior to the month of earnings announcement. The x-axis represents the ten earnings surprise deciles. The y-axis represents the size-adjusted buy-and-hold abnormal return from two days after quarter t earnings announcement through one day after quarter t+1 earnings announcement. See Appendix 1 for variable definitions

Figure 2.
PEAD returns with and without LTG forecasts

SUE deciles	DLTGISS = 1 ARQ	DLTGISS = 0 ARQ
Lowest	−0.007	−0.023
	(−0.797)	(−2.493)
2	−0.010	−0.023
	(−1.915)	(−4.172)
3	−0.005	−0.014
	(−1.188)	(−3.142)
4	−0.005	−0.011
	(−1.454)	(−2.810)
5	−0.001	−0.009
	(−0.352)	(−1.965)
6	0.001	0.004
	(0.265)	(0.742)
7	0.005	0.011
	(1.579)	(2.062)
8	0.007	0.016
	(1.797)	(3.693)
9	0.008	0.023
	(1.751)	(4.893)
Highest	0.015	0.044
	(2.115)	(3.819)
Highest – Lowest	0.022	0.067
	(2.734)	(8.515)

Note(s): This table reports the average size-adjusted returns for portfolios formed based on SUE deciles and the presence of LTG forecasts (using independent sorting). See Appendix 1 for variable definitions. T-statistics are reported in parentheses and are calculated as the time-series of the quarterly portfolio size-adjusted stock returns. ***, ** and * indicate significantly different from zero at the 1%, 5% and 10% level, respectively

Table 3. Portfolios formed based on SUE deciles and the presence of LTG forecasts

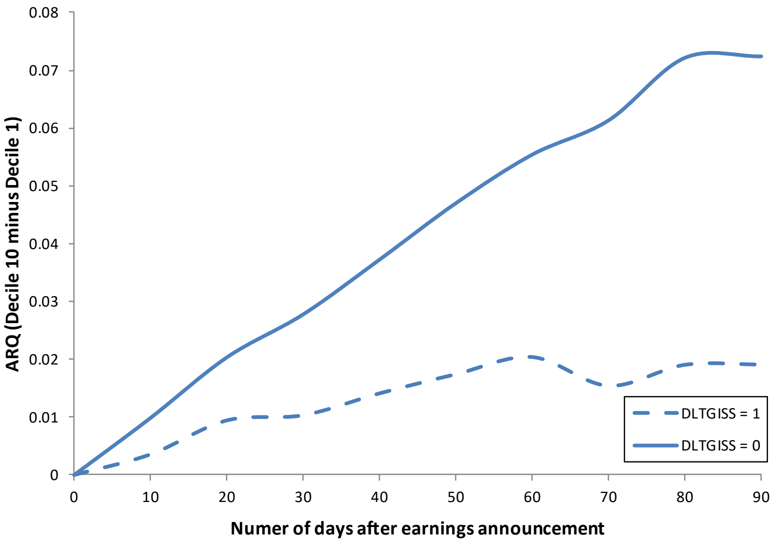
dispersion (PDISP), price (PPRICE), institutional ownership (PINST), loss (LOSS), the fourth fiscal quarter (QTR4), earnings volatility (PEVOL) and short-term forecast responsiveness (DSTERESP).

The main variable of interest in Model 1 is the interaction between SUE deciles (PSUE) and DLTGISS. The $\alpha 3$ coefficient indicates the association between the firm-level presence of LTG forecasts and PEAD returns. If the presence of LTG forecasts is associated with lower PEAD returns, we should observe that $\alpha 3$ in Model 1 is negative and significant.

Following prior literature (Zhang, 2012), I construct PSUE by transferring SUE into decile ranks by calendar quarters using cut-off values from the previous quarter and then scaling to the range −0.5 to 0.5. This transformation enables the coefficient of PSUE to be interpreted as the size-adjusted return from a zero investment strategy that longs the highest SUE decile and shorts the lowest SUE decile.

All control variables are transferred into decile ranks the same way as PSUE. The control variables PSIZE and PDISP are to capture information uncertainty (Zhang, 2012). PPRICE is to capture transaction costs (Bhushan, 1994). INST is to capture investor sophistication (Bartov *et al.*, 2000). LOSS, QTR4 and PEVOL are to capture cross-sectional variations in SUE persistence (Rangan & Sloan, 1998; Narayanamoorthy, 2006; Cao & Narayanamoorthy, 2012). DSTERESP is to capture analysts' short-term forecast responsiveness (Zhang, 2008). The model includes fixed year and industry effects to account for cross-year and cross-industry differences in the average size-adjusted returns.

Table 4 reports the multivariate regression results testing the effect of firm-level presence of LTG forecasts on PEAD returns. In Column 1, the coefficient of PSUE is 0.041, similar in magnitude to those reported in prior literature (e.g. Ayers, Li, & Yeung, 2011). The coefficient



Note(s): This figure depicts the difference in ARQ between top and bottom SUE decile over different time horizons (after earnings announcement) by whether or not the firm has LTG forecasts in the month prior to the month of earnings announcement. The x-axis represents the number of days after the earnings announcement date. The y-axis represents the difference in ARQ between top and bottom SUE decile, averaged over 76 calendar quarters from 1995 till 2013. See Appendix 1 for variable definitions

Figure 3.
Performance of drift at different horizons

	ARQ (1)	(2)	(3)
PSUE	0.041***	0.060***	0.060***
	(18.689)	(16.987)	(9.134)
DLTGISS		−0.001	−0.001
		(−0.473)	(−0.692)
PSUE*DLTGISS		−0.038***	−0.013**
		(−8.667)	(−2.253)
Controls1			Included
PSUE*Controls1			Included
Year dummies	Included	Included	Included
Industry dummies	Included	Included	Included
Observations	219,098	219,098	157,782
R-squared	0.005	0.005	0.010

Note(s): This table reports the regression results testing the relationship between the ex-ante presence of LTG forecast and PEAD returns. See Appendix 1 for variable definitions. Models are estimated using ordinary least squares regression with standard errors clustered at the firm level. *T*-statistics are reported in parentheses. ***, ** and * indicate significantly different from zero at the 1%, 5% and 10% level, respectively

Table 4.
The presence of LTG forecasts and PEAD returns

of PSUE*DLTGISS is negative and significant (−0.038) in Column 2, indicating lower PEAD returns for firms with LTG forecasts. The results are robust after controlling for a wide range of variables shown in prior studies to be associated with PEAD (Column 3).

5. Explaining the LTG forecast effect

5.1 Forecast informativeness hypothesis

Forecast informativeness hypothesis states that LTG forecasts convey value-relevant information that facilitates investors' processing of earnings information and thus mitigate PEAD. One testable prediction that comes out of this hypothesis is that, if it is the information that is conveyed through LTG forecasts that facilitates market efficiency, the timing of LTG forecast revisions should matter for these forecasts to have an effect on PEAD. Specifically, as new information is conveyed through forecast revisions, only timely LTG forecast revisions after earnings announcements can potentially help mitigating PEAD and not forecast revisions that happen long before or long after earnings announcements. In other words, if the relationship between the presence of LTG forecasts and PEAD returns is due to LTG forecasts being informative, we would expect that for a sample of firm-quarters with responsive short-term analyst forecast revisions, the magnitude of PEAD is smaller for firms that also have responsive LTG forecast revisions.

To test this prediction, I estimate the following model using ordinary least squares regression with standard errors clustered at the firm level:

$$\begin{aligned}\mathrm{ARQ}_{i,t+1} = \alpha_0 + \alpha_1\mathrm{PSUE}_{i,t} + \alpha_2\mathrm{DLTGRESP}_{i,t} + \alpha_3\mathrm{PSUE}_{i,t} * \mathrm{DLTGRESP}_{i,t} \\ + \mathrm{Controls2}_{i,t} + \mathrm{PSUE}_{i,t} * \mathrm{Controls2}_{i,t} + \mathrm{Year\ Controls} \\ + \mathrm{Industry\ Controls} + \varepsilon_{i,t+1}\end{aligned} \tag{2}$$

where

Controls2 = a vector of control variables that were included in *Controls*1, excluding short-term forecast responsiveness (DSTERESP). DSTERESP is excluded because the sample is already restricted to firm-quarters with responsive analyst short-term forecast revisions.

The main variable of interest in Model 2 is the interaction between SUE deciles (PSUE) and DLTGRESP. The $\alpha 3$ coefficient indicates the association between the responsiveness of LTG forecasts and PEAD returns. If the responsiveness of LTG forecasts is associated with lower PEAD returns, we should observe that $\alpha 3$ in Model 2 is negative and significant.

Table 5 reports the regression results testing whether the magnitude of PEAD is smaller for firms with responsive LTG forecast revisions. The coefficient of PSUE is 0.028 in Table 5 Column 1, much smaller than that in Table 4 Column 1, suggesting lower PEAD returns for firms with responsive analysts' short-term forecasts. The coefficient of PSUE*DLTGRESP is negative and significant (−0.02) in Table 5 Column 2, but lost its significance after adding the control variables in Column 3. Untabulated results show that in a regression with only two interaction terms, PSUE*DLTGRESP and PSUE*PSIZE, the interaction with DLTGRESP is not significant. This suggests that DLTGRESP does not have any effect on PEAD return beyond the effect of size. These findings are inconsistent with the prediction that LTG forecasts convey information that mitigates PEAD. These suggest that the forecast informativeness hypothesis is probably not the story that explains the negative association between the presence of LTG forecasts and PEAD returns.

5.2 Analyst ability hypothesis

Analyst ability hypothesis states that the presence of LTG forecasts indicates higher analysts' short-term forecast efficiency; and to the extent that inefficient analysts' short-term forecasts

	(1)	ARQ (2)	(3)
PSUE	0.028***	0.032***	0.031***
	(11.626)	(11.561)	(9.703)
DLTGRESP		0.007***	0.007***
		(4.893)	(4.592)
PSUE*DLTGRESP		−0.020***	−0.005
		(−3.866)	(−0.956)
Controls2			Included
PSUE*Controls2			Included
Year dummies	Included	Included	Included
Industry dummies	Included	Included	Included
Observations	140,278	140,278	120,092
R-squared	0.005	0.005	0.008

Note(s): This table reports the regression results testing the relationship between the responsiveness of LTG forecast revisions after earnings announcements and PEAD returns. See Appendix 1 for variable definitions. Models are estimated using ordinary least squares regression with standard errors clustered at the firm-level. T-statistics are reported in parentheses. ***, ** and * indicate significantly different from zero at the 1%, 5% and 10% level, respectively

Table 5. LTG forecast responsiveness and PEAD returns

contribute to PEAD or that efficient analysts' short-term forecasts mitigate PEAD, the presence of LTG forecasts relates to lower PEAD by identifying firms with more efficient analysts' short-term forecasts. Following prior literature, I examine analysts' forecast efficiency from two aspects: forecast timeliness (Zhang, 2008) and the correlation between forecast errors and SUE (Abarbanell & Bernard, 1992). The testable predictions associated with this hypothesis are that, for firms with LTG forecasts, analysts' short-term forecasts should be timelier, and the correlation between analyst forecast errors and SUE should be smaller.

5.2.1 The presence of LTG forecasts and short-term forecast responsiveness. To examine whether analysts' short-term forecast revisions are timelier for firms with LTG forecasts, I follow Zhang (2008) and estimate the following logit model with standard errors clustered at the firm level:

$$Prob(\text{DSTERESP}_{i,t} = 1) = f(\alpha_0 + \alpha_1 \text{DLTGISS}_{i,t} + \text{Controls3}_{i,t} + \text{Year Controls} + \text{Industry Controls} + \varepsilon_{i,t}) \quad (3)$$

where

Cotrols3 = a vector of control variables that were shown in prior literature to affect analyst short-term forecast responsiveness (DSTERESP). These variables are LNSIZE, AGE, EVOL, ALTMANZ, LOSS, MERGE, SPECIAL, STENUM, QTR4, BNEWS, BM, DRD, INST, EXP, NUMFIRM, DCFISS, BSIZE, LNVOLUME and PERCLTG. These are also the same group of variables that I include in Model 0 to be the determinants of DLTGISS.

The main variable of interest in Model 3 is DLTGISS. The $\alpha 1$ coefficient indicates the association between the presence of LTG forecasts and the likelihood of analysts' short-term forecast responsiveness. If the presence of LTG forecasts is associated with higher analysts' short-term forecast responsiveness, we would observe that $\alpha 1$ in Model 3 is positive and significant. Table 6 Panel A reports the regression results. The coefficient of DLTGISS is positive and significant (0.366), indicating that the presence of LTG forecasts is associated with higher analysts' short-term forecast responsiveness.

Panel A: The presence of LTG forecasts and analysts' short-term forecast responsiveness	DSTERESP
DLTGISS	0.366***
	(11.434)
Controls3	Included
Year dummies	Included
Industry dummies	Included
Observations	123,650

Panel B: The presence of LTG forecasts on the relation between analysts' forecast errors and SUE

	FE1		FE2	
	(1)	(2)	(3)	(4)
SUE	0.062***	0.053***	0.053***	0.048***
	(6.635)	(4.921)	(6.270)	(4.911)
DLTGISS		0.003***		0.003***
		(7.802)		(7.699)
SUE*DLTGISS		0.023		0.012
		(1.231)		(0.702)
Year dummies	Included	Included	Included	Included
Industry dummies	Included	Included	Included	Included
Observations	175,865	175,865	175,865	175,865
R-squared	0.019	0.020	0.018	0.019

Note(s): This table reports the regression results testing the relationship between the ex-ante presence of LTG forecasts and analyst forecast efficiency. Panel A reports the logit regression results testing the relationship between the presence of LTG forecasts and the responsiveness of analysts' short-term forecast revisions after earnings announcements. Panel B reports the ordinary least squares regression results testing the effect of the presence of LTG forecasts on the relation between analysts' short-term forecast errors and SUE. See Appendix 1 for variable definitions. Models are estimated with standard errors clustered at the firm level. z(or *t*)-statistics are reported in parentheses. ***, ** and * indicate significantly different from zero at the 1%, 5% and 10% level, respectively

Table 6. The presence of LTG forecasts and analysts forecast efficiency

5.2.2 The presence of LTG forecasts and the correlation between analysts' forecast errors and SUE. To examine whether the correlation between analysts' short-term forecast errors and earnings surprises is smaller for firms with LTG forecasts, I estimate the following ordinary least squares regression with standard errors clustered at the firm level:

$$\mathrm{FE}_{i,t} = \alpha_0 + \alpha_1 \mathrm{SUE}_{i,t} + \alpha_2 \mathrm{DLTGISS}_{i,t} + \alpha_3 \mathrm{SUE}_{i,t} * \mathrm{DLTGISS}_{i,t} + \text{Year Controls} + \text{Industry Controls} + \varepsilon_{i,t} \tag{4}$$

Forecast errors are measured at two points in time. FE1 is measured at the time of first forecast revisions for quarter t+1 earnings issued after quarter t earnings announcement. FE2 is measured at the time of last forecast revisions for quarter t+1 earnings issued before quarter t+1 earnings announcement. The main variable of interest in Model 4 is the interaction between SUE and DLTGISS. The $\alpha 3$ coefficient indicates the association between the presence of LTG forecasts and the correlation between analysts' forecast errors and SUE. If the presence of LTG forecasts is associated with lower correlation between analysts' forecast errors and SUE, we would observe that $\alpha 3$ in Model 4 is negative and significant.

Table 6 Panel B reports the regression results testing whether the presence of LTG forecasts is associated with the correlation between analysts' short-term forecast errors and SUE. The coefficients of SUE are positive and significant in Columns 1 and 3 (i.e. 0.062, 0.053), suggesting that analysts do not efficiently incorporate past SUE in their short-term forecasts.

The coefficients of SUE*DLTGISS are insignificant in Columns 2 and 4. This suggests that the presence of LTG forecasts is not associated with lower correlation between analysts' forecast errors and SUE. In other words, firms with LTG forecasts do not seem to have analysts who are more efficient in incorporating information in SUE.

5.2.3 Discussion. Results from testing of the analyst ability hypothesis seem to be mixed at first glance. On the one hand, the presence of LTG forecasts is associated with more responsive analysts' short-term forecast revisions. On the other hand, the presence of LTG forecasts does not indicate that analysts are more efficient in incorporating SUE into their short-term forecasts. Zhang (2008) argues that forecast responsiveness and the correlation between forecast errors and SUE captures the two aspects of analysts' forecast efficiency: time and magnitude. She also demonstrates that the two aspects are separate and uncorrelated. However, in the context of this study, if the presence of LTG forecasts predicts future PEAD returns solely due to its predictive power for future analysts' short-term forecast responsiveness, the relation between DLTGISS and PEAD returns should not be apparent after control for DSTERESP (which is not the case as shown in Table 4 Column 3). Untabulated results show that even within a sample of firms with responsive analysts' short-term forecasts, the *ex ante* presence of LTG forecasts still identify firms with high versus low future PEAD returns. I also check in the PEAD regression (Model 1) how much the effect of DLTGISS changes after controlling for DSTERESP. Results (untabulated) show that after controlling for PSUE*DSTERESP, the coefficient of PSUE*DLTGISS goes down only slightly from −0.038 to −0.033. Thus, the effect of the presence of LTG forecasts on PEAD returns seems to be driven by something beyond the effect of analysts' short-term forecast responsiveness. In summary, I interpret the results presented here as not supporting the analyst ability hypothesis as an explanation for the negative relationship between the presence of LTG forecasts and PEAD returns.

5.3 Earnings persistence hypothesis

Earnings persistence hypothesis states that the presence of LTG forecasts associates with SUE persistence; and to the extent that the presence of LTG forecasts indicates lower SUE persistence and that investors fail to understand this relation, we would observe lower PEAD returns for firms with LTG forecasts. The testable predictions that associate with this hypothesis are (1) autocorrelations in SUEs are lower for firms with LTG forecasts and (2) earnings expectations embedded in stock prices do not reflect the lower SUE persistence for firms with LTG forecasts.

5.3.1 The presence of LTG forecasts and SUE persistence. To examine whether SUE persistence is lower for firms with LTG forecasts, I estimate the following model using ordinary least squares regression with standard errors clustered at the firm level:

$$\begin{aligned}\mathrm{PSUE}_{i,t+1} = {} & \alpha_0 + \alpha_1\mathrm{PSUE}_{i,t} + \alpha_2\mathrm{DLTGISS}_{i,t} + \alpha_3\mathrm{PSUE}_{i,t} * \mathrm{DLTGISS}_{i,t} + \mathrm{Controls1}_{i,t} \\ & + \mathrm{PSUE}_{i,t} * \mathrm{Controls1}_{i,t} + \text{Year Controls} + \text{Industry Controls} + \varepsilon_{i,t+1} \qquad (5)\end{aligned}$$

where

Controls1 = a vector of control variables that were previously defined in Model 1.

The main variable of interest in Model 5 is the interaction between PSUE and DLTGISS. The $\alpha3$ coefficient indicates the association between the presence of LTG forecasts and the persistence of PSUE. If the presence of LTG forecasts is associated with lower SUE persistence, we should observe that $\alpha3$ in Model 5 is negative and significant.

Table 7 reports the regression results examining whether the persistence in earnings surprises is smaller for firms with LTG forecasts. Column 1 shows that the coefficient of

	FPSUE (1)	(2)	(3)
PSUE	0.384***	0.376***	0.387***
	(118.558)	(80.648)	(42.769)
DLTGISS		−0.008***	−0.012***
		(−5.485)	(−6.129)
PSUE*DLTGISS		0.015**	0.034***
		(2.555)	(4.495)
Controls1			Included
PSUE*Controls1			Included
Year dummies	Included	Included	Included
Industry dummies	Included	Included	Included
Observations	201,863	201,863	150,944
R-squared	0.154	0.154	0.160

Note(s): This table reports the regression results testing the relationship between the ex-ante presence of LTG forecasts and SUE persistence. See Appendix 1 for variable definitions. Models are estimated using ordinary least squares regression with standard errors clustered at the firm-level. T-statistics are reported in parentheses. ***, ** and * indicate significantly different from zero at the 1%, 5% and 10% level, respectively

Table 7. The presence of LTG forecasts and SUE persistence

PSUE is 0.384, which is comparable to these reported in prior literature (e.g. Cao & Narayanamoorthy, 2012). Contrary to the prediction, the coefficient of PSUE*DLTGISS is positive and significant in both Columns 2 and 3 (i.e. 0.015, 0.034). This suggests that it is unlikely that the negative relationship between the presence of LTG forecasts and PEAD returns is caused by investors not understanding the effect of LTG forecasts on the time-series properties of earnings.

5.3.2 Mishkin test. I further conduct a Mishkin (1983) test to formally examine whether the signs and magnitudes of PEAD returns reflect the market's understanding of the differences in SUE persistence for firms with and without LTG forecasts. Specifically, I compare the coefficients in the following equations, which are estimated simultaneously using a generalized nonlinear least squares estimation procedure:

$$\mathrm{PSUE}_{i,t+1} = \alpha_0 + \alpha_1 \mathrm{PSUE}_{i,t} + \alpha_2 \mathrm{DLTGISS}_{i,t} + \alpha_3 \mathrm{PSUE}_{i,t} * \mathrm{DLTGISS}_{i,t} + \varepsilon_{i,t+1} \tag{6}$$

$$\begin{aligned} \mathrm{ARQ}_{i,t+1} = \beta_0 + \beta_1 \big(& \mathrm{PSUE}_{i,t+1} - \alpha_0^* - \alpha_1^* \mathrm{PSUE}_{i,t} - \alpha_2^* \mathrm{DLTGISS}_{i,t} \\ & - \alpha_3^* \mathrm{PSUE}_{i,t} * \mathrm{DLTGISS}_{i,t} \big) + v_{i,t+1} \end{aligned} \tag{7}$$

Model 6 is a forecasting equation in which $\alpha 1$ captures the persistence of SUE for firms without LTG forecasts, while $\alpha 3$ captures the incremental persistence of SUE for firms with LTG forecasts. Model 7 is a pricing equation that uses stock returns to infer the SUE persistence that investors perceive. $\alpha 1^*$ is the estimate of investors' perceived SUE persistence for firms without LTG forecasts, while $\alpha 3^*$ is the estimate of investors' perceived incremental SUE persistence for firms with LTG forecasts. The cross-equation restrictions are tested using a likelihood ratio test.

Table 8 reports the Mishkin test of the earnings expectations embedded in stock prices. Panel A presents the results from jointly estimating the earnings forecasting and the pricing equation on two subsamples (firms with and without LTG forecasts) separately. The likelihood ratio test reject that $\alpha 1 = \alpha 1^*$ for both samples. However, $\alpha 1^*$ appears to be significantly larger for the sample of firms with LTG forecasts than for those without LTG forecasts (0.266 versus −0.038). Moreover, $\alpha 1^*$ in the non-LTG forecast sample is not statistically significant. This suggests that while investors for the LTG forecast firm comprehend a great part of the implication of past earnings for future earnings, investors for

Panel A: Firms with and without LTG forecasts		
Parameter	DLTGISS = 1 Estimate	DLTGISS = 0 Estimate
$\alpha1$	0.394***	0.378***
$\alpha1^*$	0.266***	−0.038
$\beta1$	0.131***	0.128***
Test of market efficiency	$\alpha1 = \alpha1^*$	$\alpha1 = \alpha1^*$
Likelihood ratio statistic	58.909	239.181
Marginal significance level	0	0

Panel B: Full sample	
Parameter	Estimate
$\alpha1$	0.378***
$\alpha1^*$	−0.034
$\alpha3$	0.016***
$\alpha3^*$	0.298***
$\beta1$	0.129***
$(\alpha1 - \alpha1^*)/\alpha1$	1.090
$((\alpha1 + \alpha3) - (\alpha1^* + \alpha3^*))/(\alpha1 + \alpha3)$	0.329
Test of market efficiency	$\alpha1 = \alpha1^*$
Likelihood ratio statistic	364.434
Marginal significance level	0
Test of market efficiency	$\alpha1 + \alpha3 = \alpha1^* + \alpha3^*$
Likelihood ratio statistic	44.93
Marginal significance level	0
Test of market efficiency	$(\alpha1 - \alpha1^*)/\alpha1 = ((\alpha1 + \alpha3) - (\alpha1^* + \alpha3^*))/(\alpha1 + \alpha3)$
Likelihood ratio statistic	106.95
Marginal significance level	0

Note(s): This table reports the regression results from nonlinear generalized least squares estimation of the stock price reaction to information in SUE. See Appendix 1 for variable definitions. The likelihood ratio statistic is distributed asymptotically as χ^2 with 1 degree of freedom. ***, ** and * indicate significantly different from zero at the 1%, 5% and 10% level, respectively

Table 8. Tests of market efficiency for firms with and without LTG forecasts

the non-LTG forecast firms follow a random walk model and do not incorporate at all the implications of past SUE. Panel B presents the results from the full sample. The likelihood ratio test rejects that $\alpha1 = \alpha1^*$ and that $\alpha1+\alpha3 = \alpha1^*+\alpha3^*$. This indicates that the market underestimates the persistence of earnings surprises for both the LTG forecast sample and the non-LTG forecast sample. Results also show that $(\alpha1 - \alpha1^*)/\alpha1$ is significantly larger than $((\alpha1+\alpha3) - (\alpha1^*+\alpha3^*))/(\alpha1+\alpha3)$. This suggests that earnings expectations embedded in stock prices more accurately reflect the persistence of earnings surprise for firms with LTG forecasts.

5.3.3 Discussion. Overall, results from SUE persistence tests suggest the following. First, SUE persistence is not lower, but higher, for firms with LTG forecasts. Second, the negative relationship between the presence of LTG forecasts and PEAD returns is not due to investors not understanding the effect of LTG forecasts on SUE persistence. On the contrary, it is related to more sophisticated investor understanding for the time-series properties of earnings for firms with LTG forecasts.

5.4 Controlling for the determinants of the presence of LTG forecasts

Table 9 Panel A reports the regression results examining the relationship between the presence of LTG forecasts and PEAD returns, after controlling for the observable

Panel A: Including determinants of the presence of LTG forecasts as control variables	ARQ
PSUE	0.272***
	(8.110)
DLTGISS	−0.004**
	(−2.089)
PSUE*DLTGISS	−0.024***
	(−3.769)
Controls3	Included
PSUE*Controls3	Included
Year dummies	Included
Industry dummies	Included
Observations	150,447
R-squared	0.010
Panel B: Use residual probability of the presence of LTG forecasts (RESIDUAL) in place of DLTGISS	
PSUE	0.029***
	(11.038)
RESIDUAL	−0.003
	(−1.629)
PSUE*RESIDUAL	−0.020***
	(−2.709)
Year dummies	Included
Industry dummies	Included
Observations	150,447
R-squared	0.004

Note(s): This table reports the regression results controlling for the determinants of LTG forecasts. See Appendix 1 for variable definitions. Panel A reports OLS regression results which incorporate determinants of the firm-level presence of LTG forecasts as control variables. Panel B reports OLS regression results which use the residual probability from the logit regression (RESIDUAL) in place of DLTGISS. *T*-statistics are reported in parentheses. ***, ** and * indicate significantly different from zero at the 1%, 5% and 10% level, respectively

Table 9.
Controlling for the determinants of LTG forecasts

determinants of DLTGISS identified in Model 0, as well as their interactions with PSUE. The coefficient of PSUE*DLTGISS remains negative and significant (−0.024), suggesting that the relationship between DLTGISS and PEAD is not subsumed by any of the firm-level determinants of DLTGISS. Table 9 Panel B reports the PEAD regression results replacing DLTGISS with RESIDUAL, the residual from the logit regression of DLTGISS on all of its determinants. The coefficient of PSUE*RESIDUAL is negative and significant (−0.02), suggesting that the relationship between DLTGISS and PEAD is driven by the part of information in DLTGISS that is orthogonal to its determinants.

6. Conclusion

This study examines whether and why the firm-level presence of LTG forecasts is associated with future PEAD returns. Using a sample of firm-quarters from 1995 to 2013 with analysts' short-term forecasts, I find that the magnitude of PEAD is significantly smaller for firms with LTG forecasts. I further explore three nonexclusive hypotheses about the sources of this return predictability. Results suggest that the negative relationship between the presence of LTG forecasts and PEAD returns is not driven by LTG forecasts playing a direct role in facilitating market efficiency. Further, results are inconsistent with the association between the presence of LTG forecasts and analysts' short-term forecast ability as an explanation for the relationship. Finally, there is no indication that the association between the presence of LTG forecasts and the time-series properties of earnings drives the results. The results are robust after controlling for a wide range of explanatory variables for PEAD returns or for the presence of LTG forecasts. I conclude that the finding of a negative relationship between the presence of LTG forecasts and PEAD returns documented in this study may be due to the presence of LTG forecasts capturing some unobservable firm characteristics beyond those identified in prior studies. And I leave the further investigation of these characteristics to future research.

To summarize, this study documents a negative relationship between the firm-level presence of LTG forecasts and PEAD returns. The findings from this study extend the PEAD literature by identifying a novel analyst-based predictor of the cross-sectional variations in PEAD returns. This study also advances our understanding of LTG forecasts by showing that the presence of LTG forecasts is an indicator of analysts' short-term forecast responsiveness, as well as SUE persistence.

Notes

1. Analysts' short-term forecast efficiency is measured from two aspects: time and magnitude. Following Zhang (2008), I use the responsiveness in analysts' short-term forecast revisions to capture the time aspect of analysts' short-term forecast efficiency. Following Abarbanell & Bernard (1992), I use the correlation between analysts' short-term forecast errors and SUE to capture the magnitude aspect of analysts' short-term forecast efficiency.
2. There are two general ways to calculate SUE: random-walk-based SUE and analyst-based SUE. I focus in this paper on the random-walk-based SUE. Several studies show that there is a difference between random-walk-based and analyst-based PEAD (Ayers *et al.*, 2011; Kovacs, 2016; Livnat & Mendenhall, 2006): the random walk-based PEAD is likely a result of investors misestimating the time-series properties of earnings, while the analyst-based PEAD is likely caused by longer price discovery process after earnings announcements. Thus, my results may not extend to analyst-based PEAD.

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Appendix 1

Variables	Descriptions
Main variables:	
ARQ	Size-adjusted buy-and-hold return in the drift window, defined as the raw return (two days after quarter t earnings announcement date through one day after quarter t+1 earnings announcement date) adjusted for the same period returns for the size decile for which the firm belongs (where size deciles are determined by the total market capitalizations on the earnings announcement date).
SUE	Standard unexpected earnings, defined as quarter t's EPS minus quarter $t-4$'s EPS, scaled by the stock price at the end of quarter $t-1$.
PSUE	SUE deciles, defined as SUE transferred into decile ranks within each calendar quarter using the cut-off values from the previous quarter, and then scaled to the range −0.5 to 0.5.
FPSUE	SUE deciles for quarter t+1.
DLTGISS	= 1 if more than one analyst issues LTG forecasts for firm i in the month prior to the month of quarter t earnings announcement, and 0 otherwise.
DLTGRESP	= 1 if at least one analyst revises her LTG forecast for firm i within two trading days after quarter t earnings announcement (i.e. trading days 0 and 1 with respect to the announcement date), and 0 otherwise.
DSTERESP	= 1 if at least one analyst revises her forecast for quarter t+1 of firm i within two trading days after quarter t earnings announcement (i.e. trading days 0 and 1 with respect to the announcement date), and 0 otherwise.
ABSFE1	Median absolute forecast error measured at the first forecast revisions for quarter t+1 issued after quarter t earnings announcement; where forecast error is calculated as the I/B/E/S actual EPS for quarter t+1 minus individual analysts' forecast for quarter t+1, scaled by the stock price at the end of fiscal quarter t.
ABSFE2	Median absolute forecast error measured at the last forecast revisions for quarter t+1 issued before quarter t+1 earnings announcement; where forecast error is calculated as the I/B/E/S actual EPS for quarter t+1 minus individual analysts' forecast for quarter t+1, scaled by the stock price at the end of fiscal quarter t.
FE1	Median forecast error measured at the first forecast revisions for quarter t+1 issued after quarter t earnings announcement; where forecast error is calculated as the I/B/E/S actual EPS for quarter t+1 minus individual analysts' forecast for quarter t+1, scaled by the stock price at the end of fiscal quarter t.
FE2	Median forecast error measured at the last forecast revisions for quarter t+1 issued before quarter t+1 earnings announcement; where forecast error is calculated as the I/B/E/S actual EPS for quarter t+1 minus individual analysts' forecast for quarter t+1, scaled by the stock price at the end of fiscal quarter t.
Control variables:	
SIZE	Market capitalization at the end of fiscal quarter t.
PSIZE	SIZE deciles, defined as SIZE transferred into decile ranks within each calendar quarter using the cut-off values from the previous quarter, and then scaled to the range −0.5 to 0.5.
DISP	Analyst forecast dispersion, defined as the standard deviation of one-quarter-ahead analyst forecasts divided by the stock price at the end of fiscal quarter t.
PDISP	DISP deciles defined as DISP transferred into decile ranks within each calendar quarter using the cut-off values from the previous quarter and then scaled to the range −0.5 to 0.5.

(*continued*)

Table A1.
Variable definition

Variables	Descriptions
PRICE	Market price per share at the end of fiscal quarter *t*.
PPRICE	PRICE deciles, defined as PRICE transferred into decile ranks within each calendar quarter using the cut-off values from the previous quarter, and then scaled to the range −0.5 to 0.5.
INST	Institutional ownership, defined as the percent of firm i's common shares held by institutional investors for the quarter before quarter *t* earnings announcement; where the institutional ownership information is obtained from CDA/Spectrum, and missing institutional ownership data is counted as zero.
PINST	INST deciles, defined as INST transferred into decile ranks within each calendar quarter using the cut-off values from the previous quarter, and then scaled to the range −0.5 to 0.5.
LOSS	= 1 if quarter t's earnings are negative, and 0 otherwise.
QTR4	= 1 if quarter *t* is the fourth quarter of the fiscal year, and 0 otherwise.
EVOL	Earnings volatility, defined as the standard deviation of the most recent eight quarterly earnings (including quarter *t*), while quarterly earnings are deflated by average total assets.
PEVOL	EVOL deciles, defined as EVOL transferred into decile ranks within each calendar quarter using the cut-off values from the previous quarter, and then scaled to the range −0.5 to 0.5.
LNSIZE	The natural logarithm of SIZE.
AGE	Number of years firm *i* has been publicly traded, per CRSP files.
ALTMANZ	Altman's (1968) Z-score, defined as 1.2*net working capital/total assets + 1.4*retained earnings/total assets + 3.3*earnings before interest and taxes/total assets + 0.6*market value of equity/book value of liabilities + 1*sales/total assets.
MERGE	= 1 if firm *i* experienced a merger or acquisition in quarter *t*, and 0 otherwise; where mergers or acquisitions are identified by quarterly footnote 1 of AA in compustat.
SPECIAL	= 1 if firm *i* reports negative special items in quarter *t*, and 0 otherwise.
STENUM	Number of analysts who issue one-quarter-ahead forecasts for firm *i* at the month of quarter *t* earnings announcement.
BNEWS	= 1 if the SUE of firm *i* in quarter *t* is negative, and 0 otherwise.
BM	Book-to-market ratio, defined as the book value of equity at the end of quarter *t* divided by the market value at the end of the same quarter.
RD	R&D intensity, defined as R&D expense divided by market capitalization at the end of quarter *t*; where missing R&D is counted as zero.
DRD	= 1 if RD does not equal zero, and 0 otherwise.
EXP	Median firm-specific experience of analysts who follow firm *i* for quarter *t*; where experience is measured as the number of years for which an analyst has followed the firm.
NUMFIRM	Median number of firms followed by analysts who follow firm *i* in quarter *t*.
PERCLTG	Median likelihood of issuing LTG forecasts for analysts who follow firm *i* in quarter *t*; where likelihood for each analyst is measured as number of LTG forecasts the analyst issues minus one (other than the LTG forecast issued for firm *i*), divided by the total number of firms followed by the analyst minus one (other than firm *i*).
DCFISS	= 1 if at least one analyst issues a cash flow forecast for firm *i* in the month prior to the month of quarter *t* earnings announcement, and 0 otherwise.
BSIZE	Median size of the brokerage houses employing analysts who follow firm *i* for quarter *t*; where the brokerage house size is measured as the number of distinct analysts providing forecasts in the brokerage house.
LNVOLUME	The natural logarithm of the dollar trading volume in the year prior to the year of quarter *t* earnings announcement; where dollar trading volume is measured as the absolute value of month-end stock price multiply by the trading volume during the month, summed over the 12 months.
RESIDUAL	The residual from estimating Model 0.

Table A1.

Appendix 2

Determinants of the presence of LGT forecasts

The issuance of LTG forecasts is not exogenous. Analysts make the decision of whether or not to issue LTG forecasts based on the costs and benefits of such actions. The decision is also subject to analysts' time and resource constraints. The determinants of the issuance of LTG forecasts may also be correlated with PEAD returns, causing correlated omitted variable problem which may bias my coefficient estimates. Thus, it is important that I control for these variables in my regressions. Based on the work of Jung, Shane and Yang (2008), Jung *et al.* (2012) and Zhang (2008), I discuss below some possible determinants of the issuance of LTG forecasts. As these determinants will be control variables in the PEAD tests, all variables are constructed at the firm level.

2.1 Costs-related determinants of LTG forecast issuance

The major cost for issuing LTG forecasts is the cost associated with collecting and interpreting long-term oriented information. Such cost is influenced by the information environment of firms and is lower for firms with more abundant information from various sources and lower information uncertainty. Thus, analysts are more likely to issue LTG forecasts for these firms. I discuss ten variables that are expected to capture the information environment of firms: size, age, earnings volatility, financial health (Altman's Z-score), loss occurrence, M&A, restructuring, number of analysts who issue short-term forecasts for the firm, fourth quarter earnings announcements and bad news.

Size (SIZE): Larger firms are expected to have a richer information environment and lower information uncertainty, and thus the cost of providing LTG forecasts for these firms is lower. In addition, from the benefit perspective, the demand for analyst services likely increases with firm size, since firms larger in size are expected to have a larger number of shareholders. However, size may also negatively affect the issuance of LTG forecasts. Larger firms likely have more complex corporate structures and business transactions; making it costly for analysts to interpret these information. Also, to the extent that larger firms disclose more information publicly, this could substitute analysts' forecasts and decrease the demand for LTG forecasts. Thus, the effect of SIZE on the issuance of LTG forecasts is ambiguous.

Age (AGE): Similar as size, older firms are expected to have a richer information environment and lower information uncertainty, leading to lower cost of providing LTG forecasts for these firms. However, older firms may have passed their growth stage and thus the long-term information demand for such firms may be lower. Thus, the effect of AGE is ambiguous.

Earnings volatility (EVOL): Higher earnings volatility indicates higher information uncertainty and thus higher costs for analysts to interpret information and make forecasts. Therefore, it is less likely for analysts to issue LTG forecasts for these firms.

Financial health (ALTMANZ): Following Zhang (2008, 2012), I measure financial health using Altman's (1968) Z-score. Healthy firms likely have lower information uncertainty and thus lower cost of collecting and interpreting information. Therefore, it is more likely for analysts to issue LTG forecasts for these firms.

Loss occurrence (LOSS): Firms occurring losses are more likely to be in financial distress. Information uncertainty is likely higher for these firms, resulting in higher cost of collecting and interpreting information. Also, negative earnings information is less relevant for firms' long-term earnings, as firms cannot keep losing money while remain solvent in the long run. Thus, it is less likely for analysts to issue LTG forecasts for these firms.

M&A (MERGE) and *restructuring (SPECIAL)*: Firms that have recently been through an M&A or restructuring have higher information uncertainty; thus, information interpretation costs are likely higher for these firms. However, both M&A and restructuring are events that have long-term implications for firms, and the demand for long-term oriented information is likely higher after these events. Thus, the effects of MERGE and SPECIAL on the issuance of LTG forecasts are ambiguous.

Number of analysts who issue short-term forecasts (STENUM): Analysts' forecasts are important information sources. The information environment of a firm is likely richer and the average cost of information collection lower, when a large number of analysts follows the firm. Thus, analysts are more likely to issue LTG forecasts for these firms.

Fourth quarter earnings announcements (QTR4): Studies document that fourth quarter earnings announcements provide more information than do interim announcements (Cornell & Landsman, 1989).

Thus, the information collection costs are likely lower for these earnings announcements, and analysts are more likely to issue LTG forecasts following these announcements.

Bad news (BNEWS): Negative earnings surprises likely associate with higher information uncertainty and thus higher cost of information assessment. However, to the extent that managers manage expectations to avoid negative earnings surprises (Matsumoto, 2002), these surprises, if they do occur, may convey more information about a firm's fundamentals. In addition, the demand from investors for interpreting such information, as well as the demand from managers for further guiding investors' expectations, may be higher following these surprises. Thus, the effect of BNEWS on the issuance of LTG forecasts is ambiguous.

2.2 Benefits-related determinants of LTG forecast issuance

Benefits for issuing LTG forecasts come from investors' demand for long-term oriented information. This demand is likely higher when (1) a higher percentage of a firm's value depends on long-term earnings or (2) a higher percentage of a firm's investors are long-term investors. I discuss three variables that are expected to capture the importance of long-term forecasting for a firm's valuation and the investment horizons of a firm's investors: book-to-market, R&D and institutional ownership.

Book-to-market (BM): Firms with lower BM (growth firms) likely have a higher percentage of value depend on long-term earnings; thus, demand from investors for LTG forecasts is likely higher for these firms. However, information uncertainty is also likely higher for growth firms, leading to higher cost of information collection and interpretation for these firms. Actually, prior studies based on analysts' short-term forecasts document that growth firms have lower analyst coverage (Hong, Lim, & Stein, 2000). Thus, I do not make a directional prediction on the effect of BM on the issuance of LTG forecasts.

R&D (RD): The benefits of R&D materialize in the long term; thus, firms with higher R&D expenditures (as a percentage of market capitalization) likely have a higher percentage of value depend on long-term earnings. However, the outcomes of R&D are hard to predict, and firms with high R&D intensity likely have higher information uncertainty, leading to higher cost of information interpretation for these firms. Thus, the effect of RD on the issuance of LTG forecasts is ambiguous.

Institutional ownership (INST): Institutional investors are sophisticated investors who have longer investment horizons; thus, firms with higher institutional ownership are likely the ones with higher percentage of long-term investors. Therefore, it is more likely for analysts to issue LTG forecasts for these firms.

2.3 Constraint-related determinants of LTG forecast issuance

Constraints for issuing LTG forecasts come from the limited resource, time and intellect that analysts possess. I discuss six variables that are expected to capture the constraints that analysts face: analyst experience, number of firms that an analyst follows, analysts' issuance of cash flow forecasts, broker size, a firm's trading volume and analysts' issuance of LTG forecasts for other firms.

Analyst experience (EXP): Analysts with more experience are likely more capable and face less intellect constraint for issuing LTG forecasts. Also, experienced analysts can rely on their previous experience and thus have lower marginal cost of issuing forecasts. Therefore, firms followed by experienced analysts are more likely to have LTG forecasts.

Number of firms followed by analysts (NUMFIRM): Given the time constraint that analysts face (i.e. a person can at most work 24 hours a day), analysts who follow a large number of firms are less likely to have additional time to engage in optional forecast activities, e.g. LTG forecasts. Thus, firms with analysts who follow a large number of firms are less likely to have LTG forecasts.

Analysts' issuance of cash flow forecasts (DCFISS): Similar as LTG forecasts, analysts' cash flow forecasts are another example of optional forecasts. Analysts who issue cash flow forecasts likely face less time/intellect constraint; thus, these analysts are more likely to issue LTG forecasts. However, given the time constraint, analysts who spend time on cash flow forecasts may have less time to spend on LTG forecasts. Thus, the effect of DCFISS on the issuance of LTG forecasts is ambiguous.

Broker size (BSIZE): Large brokerage firms have more resources (e.g. research support and management connections), and analysts who work for these firms likely face less resource constraint. Thus, firms with analysts from large brokerage firms are likely to have LTG forecasts.

Trading volume (VOLUME): Studies document that trading volume is a proxy for brokerage commissions (Alford & Berger, 1999). Stocks with high trading volume likely generate more brokerage commissions, and thus brokerage firms are likely to allocate more resources to these stocks. Therefore, it is more likely for analysts to issue LTG forecasts for these firms.

Analysts' issuance of LTG forecasts for other firms (PERCLTG): Analysts who are more likely to issue LTG forecasts for other firms likely face less resource, time and intellect restraints for issuing LTG forecasts. Thus, firms with analysts who are more likely to issue LTG forecasts for other firms are likely to have LTG forecasts.

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