Extrapolation Bias in Explaining the Asset Growth Anomaly: Evidence from Analysts' Multi-period Earnings Forecasts*

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Abstract

Using analysts' multi-period earnings forecasts, this paper investigates whether analyst forecast errors are related to asset growth and, if so, to what extent analysts' optimism for high-growth firms can explain the asset growth anomaly. We find that analyst forecasts are more optimistic for firms with high asset growth, particularly for longer-term forecasts (e.g., two- and three-year-ahead forecasts than one-year-ahead forecasts). We also find that analysts' optimism for high-growth firms is more pronounced for (1) firms that have maintained similar levels of growth in recent periods, (2) firms with higher information uncertainty, and (3) forecasts with longer forecast horizons (e.g., forecasts issued far before fiscal year end). Adding forecast errors to a growth-return regression substantially reduces the coefficient on asset growth, suggesting an important role of forecast errors in the growth anomaly. Path analysis suggests that analysts' long-term forecast errors, but not short-term forecast errors, are important mediators through which biased expectations about asset growth are incorporated into stock returns. Overall, our findings support the extrapolation bias explanation for the asset growth anomaly.

Keywords: analyst forecast, growth anomaly, extrapolation bias

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I. INTRODUCTION

An empirical regularity that has provoked sharp debate in the literature is the negative relation between asset growth and subsequent stock returns (i.e., the asset growth anomaly). For example, Cooper et al. (2008) find that the asset growth effect is robust to controlling for other growth measures, such as book-to-market (B/M) ratios, growth in sales (Lakonishok et al. 1994), accruals (Sloan 1996), growth in net operating assets (Hirshleifer et al. 2004), because asset growth captures all the subcomponents of growth from a firm’s investment and financing activities. Although some papers suggest that this asset growth effect merely reflects risk (e.g., Watanabe et al. 2013), a number of papers support the mispricing view that it evidences systematic bias in the market expectations about the implications of current growth for future performance (Cooper et al. 2008; Lipson et al. 2011; Mao and Wei 2015).

The extrapolation bias hypothesis has been central in support of the mispricing explanation of the asset growth effect. It suggests that investors tend to extrapolate past information too far into the future and therefore form biased expectations regarding a firm’s economic prospects (De Bondt and Thaler 1985; Lakonishok et al. 1994). The key to proving the presence of extrapolation bias is thus to document how investors extrapolate their expectation in projecting a series of future cash flows at a given level of asset growth. However, none of prior studies thoroughly link current asset growth to the multi-period cash flow projections. This paper aims to fill this void in the literature.

To demonstrate the role of extrapolation bias in the asset growth anomaly, we investigate whether analyst forecast errors are related to asset growth and, if so, to what extent analysts’ optimism for high-growth firms can explain the asset growth anomaly. Because investors’ expectations are unobservable, we use analysts’ earnings forecasts as a direct and observable proxy of the market’s expectations of future firm performance. More importantly, we utilize analyst forecasts issued for different periods (e.g., one-, two-, and three-year-ahead forecasts and long-term growth forecasts) to assess analysts’ biases in forming short-term versus long-term forecasts. Given that it takes multiple years for corporate investment to payoff, observing how analysts plug the current investment information in their multi-period earnings forecasts provides an excellent setting to examine the role of extrapolation bias. Specifically we examine how analysts assess the implications of current investment for short-term and long-term payoffs and how short-term versus long-term forecast errors affect the growth-return relation.

Using a U.S. sample spanning the period from 1987 to 2011, we first document that analysts issue more optimistic forecasts for high-growth firms than for low-growth firms. More importantly, we find that forecast optimism relating to high-growth firms is more severe for longer-term forecasts (e.g., two- and three-year-ahead forecast errors) than that for short-term forecasts (e.g., one-year-ahead forecast errors), consistent with bias being amplified as naïve extrapolation is applied multiple times by analysts to form long-term forecasts. Our cross-sectional tests suggest that the growth-anchored forecast optimism is more pronounced for firms that have maintained similar levels of growth in recent periods (i.e., there has been no reversals of growth) and for firms with higher information uncertainty, circumstances where analysts are more likely to rely on past information in projecting future earnings. In addition, the difference in forecast optimism for high-growth vs. low-growth firms gradually dissipates over time as the actual earnings announcement date approaches. Taken together, our findings are consistent with analysts anchoring current asset growth and thus extrapolating their biased expectation on future firm performance for multiple times.

While our results from analyst forecasts suggest that systematic bias exists in market expectations, these results are not conclusive about whether analysts' forecasts are a conduit through which biased expectations of information intermediaries induce another bias in investors' expectations, thereby causing the growth effect. We therefore investigate the role of analysts' optimism for high-growth firms in explaining the asset growth anomaly. We find that, when forecast errors, particularly long-term forecast errors, are included in a growth-return regression, the magnitude of the coefficient on asset growth is significantly reduced and that the magnitude of reduction is greater when longer-term forecasts are included than when short-term forecasts are included. For example, when the two-year-ahead forecast error is included in the model, the coefficient on asset growth is reduced by 66% and becomes insignificant. On the other hand, when the one-year-ahead forecast error is included, the coefficient on asset growth is reduced by 27% and is still significant. This finding is also consistent with the extrapolation bias explanation in that longer-term forecasts are more optimistic than shorter-term forecasts about value implication of asset growth.

To further substantiate the effect of extrapolation bias, we also use path analysis to quantify the role of forecast errors in the growth-return relation (i.e., an indirect link) in which forecast errors are a mediator variable through which asset growth is related to future stock returns. We find strikingly different roles of short-term versus long-term forecast errors as a mediator. Specifically, the indirect effect of one-year-ahead forecast errors is only 2% of the total growth-return relation; however, the indirect effects of long-term forecast errors (e.g., two- and three-year-ahead forecasts and long-term earnings growth forecasts) account for 21-44% of the total growth-return relation. This contrasting effect of short-term versus long-term forecasts suggests that the impact of biased expectations related to current asset growth on the mispricing of stock prices is centered on the expectations about its long-term payoffs. It also implies that focusing on only short-term forecasts in testing biased expectations in the asset growth anomaly and other related anomaly (e.g., Lipson et al. 2011) possibly understates the role of extrapolation bias in the relation between asset growth and stock returns. Overall, these findings suggest that extrapolation bias is an important factor in explaining the growth anomaly.

We examine two alternative explanations for our findings. For example, our results might be attributable to analysts' strategic behaviors to sacrifice forecast accuracy for potential benefits associated with issuing optimistically biased forecasts for growing firms, rather than analysts' cognitive bias stemming from naïve extrapolation (e.g., Dugar and Nathan 1995). Alternatively, our results might reflect analysts' failure to understand poor performance resulting from overinvestment by entrenched managers

(Titman et al. 2004, 2009). However, we do not find evidence consistent with these alternative explanations.

This study contributes to the literature on the asset growth anomaly and extrapolation bias in several ways. First, we empirically document the presence of extrapolation bias and quantify its mediating role in the asset growth anomaly. Although the extrapolation bias hypothesis has gained attention in the context of value/glamour strategy based on B/M ratios (La Porta 1996, Dechow and Sloan 1997; La Porta et al. 1997; Doukas et al. 2002), they provide mixed evidence. [1] Furthermore, these studies are rather vague about two important issues (La Porta 1996, p.1734): (1) what variable investors extrapolate and (2) how far (i.e., over what time period) they extrapolate. The asset growth anomaly provides an interesting setting for testing the extrapolation hypothesis because it specifically identifies past growth (i.e., year-on-year percentage change in total assets) as a readily available piece of information (i.e., heuristics) for investors to extrapolate. Our use of multi-period earnings forecasts provides an important insight into the time horizon of extrapolation.

Second, we contribute to the debate surrounding the underlying reasons for the asset growth anomaly by providing evidence supporting the mispricing explanation (Cooper et al. 2008; Li and Zhang 2010; Lipson et al. 2011; Mao and Wei 2015), rather than the risk-based explanation (Cochrane 1991; Berk et al. 1999; Liu et al. 2009; Li and Zhang 2010). Our approach of using analyst forecasts instead of stock returns bypasses a common limitation of prior studies that it is difficult to disentangle the effect of risk (i.e., discount rate) and that of future cash flows on a given change in stock prices. For example, naïve investors may make systematic errors in either estimating risk, or estimating future cash flows, or both (La Porta 1996), all being consistent with the mispricing explanation. Furthermore, potential market frictions such as arbitrage costs further complicate the identification in the return-based studies (Lipson et al. 2011). For example, Lam and Wei (2011) point out that proxies for limits-to-arbitrage (i.e., for the

[1] Please see Section II for more discussion on the literature on the value/glamour strategy.

mispricing explanation) and proxies for investment frictions (i.e., for the *q*-theory) are highly correlated, thereby making it difficult for researchers to distinguish between these two explanations. Thus, researchers cannot properly test the role of extrapolation bias by relying on return-based analyses, unless making a strong assumption about discount rates. For example, Lakonishok et al. (1994) assume that discount rate and payout ratios are constant in estimating expected growth rates from growth rates implied in the multiples (e.g., earnings-to-price ratio). This caveat is particularly evident in examining extrapolation bias because the implications of extrapolation bias are mainly indicative of the cash flow side, rather than the discount rate side. In contrast, analyst forecasts enable us to exclusively focus on future cash flows, and they are not affected by risk or arbitrage costs (Bradshaw et al. 2001, 2006; Kothari 2001; Doukas et al. 2002; Teoh and Wong 2002; Drake and Myers 2011; Lipson et al. 2011; Piotroski and So 2012).

The rest of the paper is organized as follows. Section 2 discusses the prior literature and Section 3 describes our research design. Section 4 presents the sample selection and descriptive statistics. Section 5 provides empirical results and Section 6 concludes.

II. PRIOR LITERATURE

It has been well documented that firms experiencing rapid growth (e.g., capital investment, accruals, sales growth, and capital raising) subsequently have abnormally low returns. A stream of research suggests that this negative relation between growth and subsequent stock returns can be explained by rational asset pricing models. Berk et al. (1999) suggest that more risky real options are converted into less risky assets-in-place when firms make investments. Therefore, firms making more investments are likely to be those with lower risk and thus lower expected returns. The *q*-theory of investment suggests that it is optimal for corporations to invest more (less) when expected returns are low (high) because more (less) investment projects become profitable when the discount rate falls (Cochrane 1991). Therefore, the negative investment-return relation is a result of optimal investment decisions by firms.[2] Consistent with this view, Wu et al. (2010) provide evidence that the negative relation between accruals and subsequent returns (i.e., the accrual anomaly) can be explained by the optimal investment hypothesis. Relying on the cross-country setting, Watanabe et al. (2013) also support the optimal investment hypothesis.

Another stream of research adopts the mispricing perspective for the growth-return relation. For example, Sloan (1996) documents the negative relation between accruals and future returns (i.e., accrual anomaly) and concludes that it is due to investors' fixation on aggregate earnings. Fairfield et al. (2003), on the other hand, argue that the accrual anomaly is due to investors' failure to understand diminishing marginal returns to investment and suggest that the accrual anomaly is a subset of a more general growth anomaly.

Most relevant to our paper, a number of prior studies on the value/glamour strategy argue that investors tend to naively extrapolate past growth too far into the future. Lakonishok et al. (1994) suggest that the value/glamour strategy produces superior returns because investors overestimate future growth rates of glamour stocks relative to value stocks based on past growth, such as sales growth. La Porta et al. (1997) show that a large fraction of abnormal returns from the value/glamour strategy is concentrated in the short window around earnings announcements as investors correct their biased expectations after earnings announcement. La Porta (1996) finds that investment strategies of selling (buying) stocks with high (low) forecasted earnings growth by analysts generate excess returns, consistent with systematic errors in expectations. While these studies are generally consistent with investors extrapolating past into the future, other studies fail to find evidence to support the extrapolation hypothesis in the value/glamour strategy (Doukas et al. 2002; Dechow and Sloan 1997). For example, Doukas et al. (2002) find that, contrary to the predictions of the extrapolation hypothesis, analysts are more optimistic about the future performance of value firms than that of growth firms.

[2] The *q*-theory predicts that the investment-return relation is more negative when investment friction is high (Li and Zhang 2010, Lam and Wei 2011).

While the value/glamour strategy literature provides insight into the role of extrapolation bias in mispricing of these stocks, Doukas et al. (2002) argue that these studies often do not directly test the extrapolation hypothesis. For example, as investors *initially* form biased expectations for value/glamour stocks under the extrapolation hypothesis, the appropriate time of testing should be just after the past year's annual report becomes available, rather than just prior to actual earnings announcement as captured in earnings announcement returns. Therefore, the method of examining the short-window market reaction around subsequent earnings announcements (La Porta 1996; La Porta et al. 1997; Cooper et al. 2008) is problematic to test the extrapolation hypothesis. Moreover, the concentration of abnormal returns around the earnings announcement period can be alternatively interpreted as growth and value stocks responding asymmetrically to negative earnings announcements. Skinner and Sloan (2002) find that growth stocks experience a stronger negative reaction to negative earnings surprises than value stock. Hence, it is possible that the return differential around subsequent earnings announcements can be due to a few large negative abnormal returns for growth stocks after negative earnings surprises (Doukas et al. 2002).

Another important limitation of the value/glamour studies in testing the extrapolation hypothesis is that they do not specifically identify the variables investors extrapolate. Many studies use B/M ratios as a sorting variable to test the extrapolation explanation in the value/glamour strategy, rather than using growth variables that investors might actually extrapolate (Lakonishok et al. 1994; Doukas et al. 2002). Furthermore, the variables often used in the value/glamour studies as extrapolating variables, such as past sales/earnings/cash flow growth, do not produce strong patterns in the cross-section of stock returns or analysts' earnings forecasts. For example, Lakonishok et al. (1994) find that the abnormal returns based on sales growth is not as dramatic as those based on B/M ratios. Likewise, using past sales growth and earnings per share (EPS) growth, Dechow and Sloan (1997) do not find evidence to support the extrapolation hypothesis. Therefore, it is possible that mixed evidence in prior work on extrapolation bias in the value/glamour strategy is related to the selection of growth variables.

In this paper, we focus on the asset growth effect in testing the extrapolation hypothesis. An advantage of the asset growth anomaly is that it specifies the growth variables that investors are likely to extrapolate: annual asset growth. A few studies on the asset growth anomaly propose extrapolation bias as an underlying channel (Cooper et al. 2008; Lipson et al. 2011; Mao and Wei 2015). For example, Cooper et al. (2008) indicate that their findings are consistent with the interpretation that investors over-extrapolate past gains to growth based on (1) the future negative (positive) operating performance for high- (low-) growth firms and (2) the abnormal stock returns around subsequent earnings announcements. However, such evidence is rather indirect, and they do not specifically test the role of extrapolation bias in the growth anomaly. Closely related to our paper, Lipson et al. (2011) examine the role of arbitrage costs (i.e., idiosyncratic volatilities) in the asset growth effect. In one of their tables, they show that analyst one-year-ahead forecasts are optimistic for firms with high growth. However, Lipson et al. (2011) do not examine forecasts for longer periods, which we document are the key mediating variables in the growth-return relation, nor do they directly link forecast errors to the growth-return relation. Moreover, they do not examine conditions under which expectation errors are exacerbated.

III. RESEARCH DESIGN

To investigate the relation between growth and analyst forecast errors, we use the year-on-year percentage change in total assets as the main empirical proxy for asset growth (Cooper et al. 2008; Lipson et al. 2011). Analyst earnings forecast errors are defined as actual earnings per share (EPS) minus the analysts' consensus (mean) forecast, scaled by the stock price at the end of fiscal year t. We obtain monthly consensus forecasts of annual earnings from the IBES summary file.

To examine how analyst forecasts for various periods are related to current asset growth, we calculate the one-, two-, and three-year-ahead earnings forecast error from the monthly IBES summary file in the first month after the year t earnings announcement. The long-term earnings growth forecast errors are defined as the realized long-term earnings growth rate minus the consensus forecast of long-term earnings growth rate, also from the monthly IBES summary file in the first month after the year *t* earnings announcement. Following Bradshaw et al. (2006), realized long-term earnings growth is calculated as the slope coefficient of a regression of the natural logarithm of realized annual EPS on a time trend using at least three EPS with a maximum of six.[3] Figures 1A and 1B illustrate the timeline of how our various measures of forecast error are constructed.

We use the following equation as a baseline model to examine the relation between asset growth and analyst forecast errors:

$$FE_{t+n} = a_0 + a_1 AG_t + a_2 WACC_t + a_3 WCFO_t + a_4 FE_{t,\,1M} \text{ (or } LTGFE_{t,\,1M}) + a_5 LOSS_t + a_6 XFIN_t + a_7 SIZE_t + a_8 BM_t + a_9 CRET_t + Industry\ /\ Year\ Fixed\ Effects + \varepsilon_t \quad (1)$$

The dependent variable (FE_{t+n}) is either a one-year-ahead forecast error ($FE_{t+1,\,1M}$), two-year-ahead forecast error ($FE_{t+2,\,1M}$), three-year-ahead forecast error ($FE_{t+3,\,1M}$), or long-term earnings growth forecast error ($LTGFE_{1M}$), all measured in the first month after the year *t* earnings announcement. Note that these forecasts are measured at the same point in time but for different forecast periods.

Our variable of interest is *AG*, which is the growth rate of total assets. We predict the coefficient on *AG* (a_1) to be negative if analysts are subject to extrapolation bias and thus issue more optimistic forecasts for high-growth firms. To assess a distinct role of asset growth above and beyond other growth/investment-related variables, such as current accruals, external financing activities, and B/M ratios, we directly control for these variables and other controls known to affect forecast errors in the multivariate models, mitigating the concern that our empirical results merely capture a spurious relation between other growth variables and analysts' forecast errors.

[3] We focus on analysts' earnings forecasts rather than their target prices because earnings forecasts directly capture the analysts' expectation about the effect of asset growth on future earnings, whereas target prices also contain the expectation about future discount rate.

We include current accruals (*WACC*) as prior studies document that analysts issue more optimistic forecasts for firms with high accruals (e.g., Bradshaw et al. 2001). Cash flows (*WCFO*) are included because accruals and cash flows are highly correlated; thus, omitting cash flows when examining the accrual effect would result in an incomplete analysis (Desai et al. 2004; Drake and Myers 2011). We also control for potential serial correlation in the forecast errors by including prior-period forecast errors ($FE_{t,1M}$ or $LTGFE_{t,1M}$ depending on the dependent variable used). We include *LOSS* because Ali et al. (1992) find that analysts are more optimistic about loss firms. *XFIN* represents external financing activities, measured as the sum of net equity issuance and net debt issuance. Bradshaw et al. (2006) document that external financing activities are positively related to optimism in analyst forecasts.[4] To control for the effect of firm size, B/M ratios, and contemporaneous stock returns, we include *SIZE*, *BM*, and *CRET* in the model. Detailed variable definitions are provided in the appendix.

IV. SAMPLE AND DESCRIPTIVE STATISTICS

4.1. Sample Selection

Our sample consists of all available firm-year observations from the combination of Compustat, CRSP, and IBES. Financial firms, firm-year observations with negative book value, and those without the information necessary to compute the variables are excluded from the sample. Our final sample covers the period from 1987 to 2011. The sample contains 70,123 firm-year observations with available asset growth and control variables but is reduced to 61,943 when we require the one-year-ahead forecast error variable and further to 13,134 when we require three-year-ahead forecast error. All variables are winsorized at the 1% and 99% levels.

4.2. Descriptive Statistics and Correlations

[4] Bradshaw et al. (2006) find that debt financing is related to optimistic short-term forecasts while equity financing is related to optimistic long-term forecasts, suggesting that the degree of optimism in specific forecasting variables is related to the type of corporate financing activities undertaken. Our empirical results are qualitatively similar when we replace net external financing (*XFIN*) with two separate variables for debt and equity issuance.

Table 1 reports the descriptive statistics of the variables used in our empirical analyses. The mean (median) value of analysts' one-year-ahead forecast error ($FE_{t+1,1M}$) is -0.032 (-0.004) and the other forecast error variables also have negative mean values, indicating that analysts issue optimistic forecasts on average. The mean value of asset growth (*AG*) is 0.166 with a standard deviation of 0.405.

[Insert Table 1 here]

Table 2 reports the correlations among the various measures of analyst forecast error, asset growth, and the control variables. The univariate correlations between asset growth (*AG*) and the measures of analyst forecast error show mixed findings. For example, *AG* is positively correlated with the one-year-ahead forecast errors ($FE_{t+1, 1M}$), while *AG* is negatively correlated with the two- and three-year-ahead forecast errors and the long-term earnings growth forecast errors. Analyst forecasts are more optimistic for loss firms, firms with more external financing activities, smaller firms, value firms, and firms with high contemporary returns. *AG* is also significantly correlated with other growth variables such as accruals, external financing, and B/M ratios.

[Insert Table 2 here]

V. EMPIRICAL RESULTS

5.1. The Effect of Asset Growth on Analyst Forecast Errors

In Table 3, we estimate Equation (1) to examine the relation between asset growth and analyst forecast errors.[5] In Column (1), when the one-year-ahead forecast error measured in the first month after the year *t* earnings announcement ($FE_{t+1, 1M}$) is used as the dependent variable, the coefficient on *AG* is negative and significant. This finding suggests that analyst forecasts are more optimistic (i.e., forecast errors are negative) for firms with high asset growth, consistent with the finding in Lipson et al. (2011).

[5] The number of observations for each column varies due to data availability for each dependent variable. For example, the number of observations for $FE_{t+3, 1M}$ in Column (3) (N = 13,134) is low compared to those in other columns because of the limited availability of three-year-ahead earnings forecasts in IBES. If we re-run the regressions for the constant sample for which all the dependent variables are available, the results are similar.

The magnitude of the coefficient (-0.009) can be interpreted as a one-standard-deviation change in asset growth increasing forecast optimism by 0.36% of the stock price (i.e., 11% of the mean of $FE_{t+1, 1M}$ or 10% of the interquartile range of $FE_{t+1, 1M}$). [6]

The results for the control variables are consistent with prior literature. The coefficient on accruals (*WACC*) is significantly negative, consistent with studies on the accruals anomaly (e.g., Bradshaw et al. 2001). The positive coefficient on prior forecast errors ($FE_{t,1M}$ or $LTGFE_{t,1M}$) indicates that analyst forecast errors are serially correlated. Analyst forecasts are generally more optimistic for firms with negative income, smaller firms, firms with high B/M ratios, and firms with high contemporaneous returns. The coefficients on *XFIN* are largely insignificant, consistent with Lipson et al.'s (2011) finding that the asset growth effect subsumes the external financing effect.[7]

To examine whether our results are driven by specific components of asset growth, we decompose asset growth into its major components from asset side and financing side of the balance sheet (Cooper et al. 2008). Specifically, we decompose asset growth into changes in cash, current asset growth, property, plant, and equipment growth, and other asset growth and re-estimate the regressions. We find that analyst forecast errors are significantly related to all components of asset growth except changes in cash (untabulated). We also split the financing side of asset growth into interest-bearing debt growth, non-interest-bearing debt (operating liabilities) growth, equity growth (equity issuance minus repurchases), and retained earnings growth. Untabulated results show that all components of asset growth, except

[6] Analysts' optimistic earnings forecasts can be due to either their optimistic sales forecasts, or optimistic estimates about future profitability (i.e., profit margin), or both. For a subsample for which sales forecasts are available from IBES, we examine whether asset growth is related to sales forecast errors (actual sales –sales forecasts) or profit margin forecast errors (actual profit margin – profit margin forecasts where profit margin is calculated as (Sales-Earnings)/Sales). Untabulated results show that asset growth is significantly related with profit margin forecast errors, while it is not significantly related to sales forecast errors, suggesting that analysts are more optimistic about future profitability for high-growth firms, but they are not overly optimistic about future sales for growth firms.

[7] When asset growth is not included in the regressions, the coefficients on *XFIN* are significantly negative. It is possible that the insignificant coefficient on *XFIN* is related to a high correlation between asset growth and external financing (0.74 in Table 2). However, we find that the VIF (variance inflation factor) is less than 10, which is the typical threshold for serious multicollinearity in the regression model. When we re-estimate the model without *XFIN*, the results are similar to those reported in Table 3. Thus, the multicollinearity problem is unlikely to cause a bias in our empirical analysis.

increases in operating liabilities, are related to analyst forecast errors, suggesting that our results are not driven by particular subcomponents of asset growth. These results are generally consistent with Cooper et al. (2008), who report that all subcomponents of asset growth, other than changes in cash, changes in operating liabilities, and changes in retained earnings, are significantly related to future stock returns.

Next, to test our prediction that analysts' optimism for high-growth firms is more pronounced for longer-term forecasts, we use the two- and three-year-ahead forecast errors measured in the first month after the year *t* earnings announcement ($FE_{t+2, 1M}$ and $FE_{t+3, 1M}$) are used as the dependent variables in Columns (2) and (3). The coefficients on *AG* are also significantly negative, suggesting that analysts issue more optimistic long-term forecasts for high-growth firms. More importantly, when the results are compared to those in Column (1), the magnitudes of the coefficients on *AG* for $FE_{t+2, 1M}$ (-0.019) and $FE_{t+3, 1M}$ (-0.020) are greater than that for $FE_{t+1, 1M}$ (-0.009), suggesting that the degree of optimism for growth firms is higher for long-term forecasts (i.e., two- and three-year-ahead forecasts) than for short-term forecasts (i.e., one-year-ahead forecasts). The test statistics presented at the bottom of the table show that the differences are statistically significant. This result supports the idea that the effect of extrapolation is amplified for long-term forecasts.

The result for long-term earnings growth forecast errors is presented in Column (4). The coefficient on *AG* is significantly negative, suggesting that analysts issue more optimistic long-term earnings growth forecasts for high-growth firms. The magnitude of the coefficient on *AG* (-0.035) in Column (4) can be translated as a one-standard-deviation change in asset growth increasing forecast optimism in long-term earnings growth rate by 1.42% (i.e., 14% of the mean of $LTGFE_{1M}$ or 6% of interquartile range of $LTGFE_{1M}$).

Overall, the results in Table 3 suggest that analysts' earnings forecasts are more optimistic for firms with high asset growth, particularly for long-term forecasts.

[Insert Table 3 here]

5.2. The Effect of Historical Growth Patterns on the Relation between Asset Growth and Analyst Forecast Errors

We expect extrapolation bias to be more pronounced for firms that have maintained similar levels of asset growth in recent periods and to be less pronounced for firms with reversals of asset growth. This is because reversals of asset growth give conflicting signals about the appropriate weight to put on historical growth and thus weaken the extrapolation associated with asset growth. In contrast, for firms that have maintained similar levels of growth in the recent periods (i.e., firms with no reversals of growth), the information has been repeatedly confirmed by subsequent information, and thus analysts are more likely to assign too much weight on the recent growth pattern in predicting future performance. To test this prediction, we first rank firms independently based on (1) the past three-year average asset growth from year t-3 to year t-1 and (2) the current asset growth. We then classify firms as having reversals of asset growth if they belong to the bottom (top) 30% based on past asset growth and the top (bottom) 30% based on current asset growth. Otherwise, firms are classified as not having reversals of asset growth.

Panel A of Table 4 reports the results for the subsample of firms without reversals of asset growth. The results are very similar to those previously reported in Table 3. In contrast, the results presented in Panel B with the subsample of firms that experienced reversals of asset growth in the recent periods, are much weaker. For example, while the coefficient on *AG* reported in Column (1) of Panel A (-0.009) is negative and significant, that in Column (1) of Panel B (-0.007) is not significant. Further, when the dependent variable is the long-term earnings growth forecast error (Columns (4) of Panels A and B), the magnitude of the coefficient on *AG* for those without asset growth reversals (-0.038) in Panel A is twice as large as that for those with asset growth reversals (-0.018) in Panel B. These findings suggest that there is little analyst optimism for high-growth firms when the high growth of the current period is preceded by a low level of past growth. In such case, analysts are less likely to extrapolate from past growth. Overall, the results in Table 4 show that the extent of analysts' extrapolation bias is affected by the recent growth patterns, supporting the prediction of the extrapolation hypothesis.[8]

[Insert Table 4 here]

5.3. The Effect of Information Uncertainty on the Relation between Asset Growth and Analyst Forecast Errors

We predict that extrapolation bias is more likely to occur for firms with a high degree of information uncertainty because analysts tend to underreact to new information and thus put more weight on past information for such firms (Zhang 2006). We follow prior studies (Zhang 2006; Chung and Chuwonganant 2014) and construct a composite index of information uncertainty (*IU*) as follows: (1) we first calculate the annual median values of firm size (market capitalization), firm age (the number of years since the firm appears CRSP), return volatility (the standard deviation of weekly stock returns during the fiscal year), cash flow volatility (the standard deviation of operating cash flows in the past five years) and then generate an indicator variable for each proxy of information uncertainty, which is equal to one for those classified as having high information uncertainty, and zero otherwise, (2) we construct an indicator variable equal to one for the years if the implied volatility of S&P 100 (VIX) offered by Chicago Board Options Exchange (CBOE) is greater than the sample median, and zero otherwise, [9] and then (3) we calculate the average values of the five indicator variables for each firm-year observation (*IU*).

To test our prediction about information uncertainty, we split the sample into two groups based on *IU* and estimate Equation (1) separately for each sample. The results are presented in Table 5. [10] In Panel A, for the low information uncertainty group, the coefficients on *AG* is insignificant when the

[8] We find similar results when we use the forecast error variables measured at other points in time ($FE_{t+2,\,12M}$, $FE_{t+2,\,24M}$, $FE_{t+3,\,12M}$, $FE_{t+3,\,24M}$, and $FE_{t+3,\,36M}$) as the dependent variable, which are to be discussed in Section 5.4.

[9] One advantage of using VIX as a proxy of information asymmetry is the mitigation of the reverse causality concern because the information uncertainty of individual firms that do not belong to S&P index would not have an impact on VIX (Chung and Chuwonganant 2014).

[10] Note that the sample size is reduced in Table 5 compared to the corresponding analysis in Table 3 because we require additional variables for information uncertainty (e.g., the volatility of operating cash flows over past five years) to be available.

dependent variable is short-term forecast error ($FE_{t+1,\ 1M}$) in Column (1). In contrast, it is significantly negative for the high information uncertainty group in Panel B. The difference in the coefficients on *AG* between the low and high information uncertainty groups is statistically significant at the 5% level. When we use longer-term forecast errors ($FE_{t+2,\ 1M}$, $FE_{t+3,\ 1M}$, and $LTGFE_{1M}$), the coefficients on *AG* are negative and significant for both high and low information uncertainty groups. However, the magnitudes of the coefficients on *AG* are greater for the high information uncertainty group than those for the low information uncertainty group; the differences are all statistically significant as reported in the lower part of the table. Overall, the findings in Table 5 are consistent with our prediction that extrapolation bias is exacerbated for firms with high information uncertainty.[11]

[Insert Table 5 here]

5.4. The Effect of Asset Growth on Analyst Forecast Errors Measured at Different Points in Time

Next, we examine how analyst forecast errors measured at different points in time are related to current asset growth. We expect optimism for high-growth firms to be lessened for forecasts with shorter forecast horizons (i.e., those issued just before actual earnings announcement) than for forecasts with longer forecast horizons (i.e., those issued far before actual earnings announcement) since analysts would rely less on extrapolation as they gain more information with which to understand the value implications of current growth. To test this prediction, we use analyst forecast errors measured at different points in time as the dependent variable, holding the forecast periods constant, and compare the coefficients on *AG* across these forecast errors. This test enables us to observe how analysts adjust their estimates about the effect of current growth on future earnings over time. Specifically, we calculate the one-year-ahead earnings forecast error using forecasts from the monthly IBES summary file in the 12th month after the year *t* earnings announcement ($FE_{t+1,\ 12M}$). The point in time for $FE_{t+1,\ 12M}$ usually corresponds to the month right before the actual year *t*+1 earnings announcement. Similarly, for the two-year-ahead earnings

[11] We find similar results when we use forecast error variables measured at other points in time ($FE_{t+2,\ 12M}$, $FE_{t+2,\ 24M}$, $FE_{t+3,\ 12M}$, $FE_{t+3,\ 24M}$, and $FE_{t+3,\ 36M}$) as the dependent variable, which are to be discussed in Section 5.4.

forecast error, consensus forecasts for year t+2 earnings are measured using the forecasts from the monthly IBES summary file in the 12th and 24th month after the year t earnings announcement ($FE_{t+2,\ 12M}$ and $FE_{t+2,\ 24M}$). For the three-year-ahead earnings forecast error, three measures of forecast error are similarly defined ($FE_{t+3,\ 12M}$, $FE_{t+3,\ 24M}$, and $FE_{t+3,\ 36M}$). Please see Figures 1A and 1B for illustration. The descriptive statistics reported in Table 1 show that the magnitudes of forecast errors are attenuated as the end of the forecasted period approaches, consistent with Bradshaw et al. (2006). For instance, the mean values of the two-year-ahead earnings forecast error decrease from -0.033 when they are measured in the first month after the year t earnings announcement ($FE_{t+2,1M}$) to -0.024 ($FE_{t+2,12M}$) and -0.004 ($FE_{t+2,24M}$) when they are measured in the 12th and 24th month after the year t earnings announcement.

Table 6 presents the results using several analyst forecast errors measured at various points in time. For ease of comparison, in Columns (1), (3), and (6), we reproduce the results for $FE_{t+1,\ 1M}$, $FE_{t+2,\ 1M}$, and $FE_{t+3,\ 1M}$, which were previously reported in Table 3.

In Column (2), when the one-year-ahead forecast error is measured 12 months after year t earnings announcement, the coefficient on *AG* (-0.002) is marginally insignificant (t = -1.62). The difference between the coefficients on *AG* for $FE_{t+1,\ 1M}$ and $FE_{t+1,\ 12M}$ is statistically significant at the 1% level.[12] This result indicates that analysts rely less on extrapolation as more information becomes available, and thus by the time actual earnings are about to be released, there is no significant optimism in one-year-ahead forecasts regarding high-growth firms.

Similar to the pattern observed for one-year-ahead forecast errors, as the end of the forecast periods approaches (i.e., as forecast horizons get shorter), the optimism in long-term forecasts about high-growth firms is also gradually attenuated. For example, the coefficients on *AG* decrease from -0.020 in Column (6) for $FE_{t+3,\ 1M}$ to -0.012, -0.005, and -0.003 in Columns (7), (8), and (9) for $FE_{t+3,\ 12M}$, $FE_{t+3,\ 24M}$, and $FE_{t+3,\ 36M}$, respectively. As presented in the lower part of Table 6, the differences in the coefficients

[12] We test the difference in the coefficients on *AG* between columns using a Wald test in the seemingly unrelated regressions model, following Zellner (1962).

on *AG* for the forecasts with different forecast horizons are statistically significant with one exception, the difference between the coefficients on *AG* for $FE_{t+3,\ 24M}$ and $FE_{t+3,\ 36M}$. Different from the result for one-year-ahead forecasts, the two- and three-year-ahead forecast errors remain optimistic for firms with high growth even by the time when actual earnings for the corresponding periods are about to be released. For example, the coefficients on *AG* are still significantly negative in Columns (5) and (9) when the dependent variable are $FE_{t+2,\ 24M}$ and $FE_{t+3,\ 36M}$, respectively. Taken together with the previous finding for one-year-ahead forecast errors, this finding suggests that analysts are initially overly optimistic about the long-term effect of current investment (i.e., the effect of year *t* investment on year *t*+2 and *t*+3 earnings); while they adjust their estimates over time, their adjustments are incomplete for the long-term effect of current investment. On the other hand, they seem to fully adjust their estimates about the short-term effect (i.e., the effect of year *t* investment on year *t*+1 earnings). Given that corporate investment made in year *t* has impacts on multiple years, this finding suggests that analysts' year *t*+1 forecasts are likely to be biased due to investment made years ago. Collectively, the results in Table 6 support our prediction that analysts' forecasts optimism is greater for those with long forecast horizons.

[Insert Table 6 here]

5.5. The Effect of Analyst Forecast Errors on the Relation between Future Stock Returns and Asset Growth

In this section we test the role of analyst forecast errors stemming from extrapolation bias in the relation between asset growth and subsequent stock returns. Prior studies suggest that several types of anomalies are linked to biased analyst forecasts. For example, Rajan and Servaes (1997) provide evidence that the initial public offering (IPO) anomaly is partially driven by analysts' over-optimistic growth forecasts. Hribar and McInnis (2012) show that adding forecast errors to a regression of stock returns on sentiment absorbs a significant portion of the explanatory power of investor sentiment for the cross-section of future returns.

To assess the effect of analyst forecast errors on the growth-return relation, we take two approaches as follows. First, we add the forecast error variables in a regression of future stock returns on asset growth and assess the impact of doing so on the coefficient on asset growth (Hribar and McInnis 2012). To the extent that analysts forecast errors capture biased expectations reflected in the stock market, we expect the negative relation between asset growth and subsequent stock returns to be attenuated when analysts forecast errors are controlled for. Second, we use path analysis to assess the relative magnitude of a direct link (path) between asset growth and stock returns, and that of an indirect link, in which forecast errors are a mediator variable that is influenced by asset growth and that, in turn, influences the future stock returns (Bhattacharya et al. 2012). If the indirect path mediated by analyst forecast errors can explain a substantial portion of the growth-return relation, it indicates that investors overact to the information of asset growth and form the biased expectation in a similar manner with analysts. In both approaches, we assess the distinct role of short-term forecast errors versus long-term forecast error by utilizing various forecast errors for different horizons.

In Panel A of Table 7, we estimate cross-sectional Fama-MacBeth (1973) regressions of monthly returns on asset growth, and analyst forecast errors after including firm size (*SIZE*), leverage (*LEV*), B/M ratio (*BM*), and momentum (*MOM*) as the control variables in the regression. The independent variables in year *t* are matched to the monthly returns for the 12-month period beginning in the fourth month of the year *t*+1. When we include asset growth with *SIZE*, *LEV*, *BM*, and *MOM* in Column (1), the coefficient on asset growth (*AG*) is significantly negative, consistent with the asset growth anomaly documented in prior studies (e.g., Cooper et al. 2008). The magnitude of the coefficient on *AG* (-0.400) indicates that a one-standard-deviation increase in asset growth is associated with a decrease of 0.16% in monthly returns (= 0.4% * 0.405).[13] In Column (2), we further include one-year-ahead forecast errors ($FE_{t+1, 1M}$) in the model. The coefficient on $FE_{t+1, 1M}$ is positive, indicating that more optimistic forecasts are associated

[13] We note that the coefficients on *MOM* are significantly negative in Columns (2) and (3), which is seemingly inconsistent with the prediction but consistent with some studies (e.g., Balachandran and Mohanram 2012).

with low subsequent returns (Hribar and McInnis 2012). The coefficient on *AG* in Column (2) is still significant, although it falls by 27% from -0.400 in Column (1) to -0.292 in Column (2) with the inclusion of $FE_{t+1,\,1M}$. This reduction in the coefficients on *AG* is not significant as presented in the lower part of the table.[14]

Next, we use the two- or three-year-ahead forecast error ($FE_{t+2,\,1M}$ and $FE_{t+3,\,1M}$) as the measure of analyst forecast error in Columns (3) and (4), respectively. We find that the coefficients on the forecast error variables are positive and significant, similar to the finding in Column (2). Different from the previous column, the coefficients on *AG* are insignificant. The impact of including long-term forecast errors on *AG* is greater that of including short-term forecast errors. Specifically, the coefficient on *AG* reduces by 66% (53%) we use the two- (three-) year-ahead forecast error. When we use the long-term earnings growth forecast errors ($LTGFE_{1M}$) as the measure of forecast error in Column (5), the coefficients on $LTGFE_{1M}$ is also positive and significant. The coefficient on *AG* is insignificant and it reduces by 95% due to the inclusion of the long-term earnings growth forecast errors. The reduction in the coefficient on *AG* is significant at the 10% level. The greater impact of long-term forecast errors ($FE_{t+2,\,1M}$, $FE_{t+3,\,1M}$, and $LTGFE_{1M}$) on the growth-return relation compared to that of short-term forecast errors ($FE_{t+1,\,1M}$) indicates that longer-term forecast errors, which are likely to reflect more extrapolation bias, have a stronger effect on the stock returns related to asset growth. This interpretation is consistent with the finding in Copeland et al. (2004) that revisions in long-term analyst forecasts have a greater influence on stock prices than do revisions in short-term forecasts.[16]

[Insert Table 7 here]

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[14] We follow Clogg et al. (1995) to check whether the reduction in the coefficients from Fama-MacBeth regression is statistically significant.

[16] The results remain largely unchanged when we use the CRSP size-adjusted returns (untabulated). When we expand the return measurement period from 12 months to 24 months or 36 months, we find that the magnitudes of the coefficients on *AG* are substantially reduced and they become insignificant or significantly positive in some cases. We also find that when we divide the sample into five groups based on firm size, leverage, B/M ratio, or momentum, the results generally hold for each subsample.

In untabulated analyses, we partition the sample into firms with asset reversals and those without reversals as in Table 4 and estimate the Fama-MacBeth regression separately for these samples. We find that the results are mainly driven by the subsample without asset reversals. For example, for the sample without asset reversals, the magnitude of the coefficient on *AG* is substantially reduced by 78% (from -0.320 to -0.071) by the inclusion of $FE_{t+1,\ 1M}$. On the other hand, it is reduced by only 35% (from -0.900 to -0.601) for the sample with asset reversals. [18]

In untabulated analyses, we check whether our inferences are affected by the availability of analyst forecast errors variables because the sample size for long-term forecasts is smaller for short-term forecasts. For example, for the tabulated results, we use 421,645, 358,898, and 113,529 firm-month observations to perform monthly regressions using $FE_{t+1,\ 1M}$, $FE_{t+2,\ 1M,}$ and $FE_{t+3,\ 1M}$, respectively. We first require $FE_{t+2,\ 1M}$ to be available, and re-estimate the regressions in Columns (1), (2), and (3). The coefficient on *AG* is -0.354 (t = -2.42) in the regression without forecast errors (i.e., baseline), and it is reduced by 36% to -0.226 (t = -1.57) when $FE_{t+1,\ 1M}$ is included. The coefficient on *AG* is reduced by 62% to -0.135 (t = -0.95) when $FE_{t+2,\ 1M}$ is included in the model.

In addition, we require $FE_{t+1,\ 1M,}$ $FE_{t+2,\ 1M}$ and $FE_{t+3,\ 1M}$ to be available and re-estimate the regressions. The coefficient on *AG* is -0.355 (t = -1.78) in the baseline model, and it is reduced by 28% to -0.255 (t = -1.32) as $FE_{t+1,\ 1M}$ is included. The coefficient on *AG* is further reduced by 55% to -0.160 (t = 0.82) as FE_{t+2} is included, and it is reduced by 47% to -0.187 (t = -0.95) as $FE_{t+3,\ 1M}$ is included. These results suggest that our inferences that the effect of long-term forecast errors on the growth-return relation is greater than that of short-term forecast errors is not affected by the availability of longer-term forecasts.

[18] As in the cross-sectional test reported in Table 5, we partition the sample into the two groups based on *IU* and repeat the analyses. We find similar findings for a high information uncertainty group. For example, for those with high information uncertainty, the coefficient on *AG* changes from -0.357 (t = -1.73) in the baseline model to -0.046 (t = -0.23) as we include $FE_{t+1,\ 1M}$ in the model. In contrast, for the sample of low information uncertainty firms, the coefficient on *AG* is insignificant even in the absence of $FE_{t+1,\ 1M}$.

Panel B of Table 7 reports the results of the path analysis. [15] In each column, we use each of the forecast error variables as a sole mediating variable in the relation between asset growth and future stock returns. The direct effect of asset growth on future return is estimated from the coefficient on asset growth in the future return regression. The indirect effect of forecast error on the growth-return relation is calculated as the product of (i) the coefficient on asset growth in the forecast error regression and (ii) the coefficient on the forecast error variable in the future return regression (see Preacher et al. 2007). Total effect is the sum of direct and indirect effects. Column (1) shows that the indirect effect of one-year-ahead forecast error is 2% and the direct effect of *AG* is 98% of the total growth and return relation, suggesting that only a small portion (i.e., 2%) of the growth-return relation is explained by the mediating role of short-term forecast error ($FE_{t+1,\ 1M}$). In stark contrast, when we use longer-term forecast errors ($FE_{t+2,\ 1M}$, $FE_{t+3,\ 1M}$, and $LTGFE_{1M}$) as the mediating factor in Columns (2) to (4), we find much greater impacts of forecast errors. For instance, when we use the two-year-ahead forecast error ($FE_{t+2,\ 1M}$) as the mediating variable, the indirect path from asset growth to future returns through long-term earnings growth forecast errors takes 29% of total relation between asset growth and stock returns. The indirect effect of three-year- ahead forecast errors and long-term earnings growth forecast errors are 21% and 44%, respectively. Statistical tests suggest that these indirect effects of long-term forecast errors are significant at the 1% level.

We also check whether our inferences are affected by the availability of analyst forecast errors variables. Untabulated results show that for the sample for which $FE_{t+1,\ 1M}$, $FE_{t+2,\ 1M}$, and $FE_{t+3,\ 1M}$ are available, the percentage of the indirect path from asset growth to future returns through $FE_{t+1,\ 1M}$ is still 2% of the total effect, The indirect effects of $FE_{t+2,\ 1M}$ and $FE_{t+3,\ 1M}$ are 29% and 21%, respectively, for this sample, suggesting that our inferences on the mediating effect of forecast error on the relation between asset growth and future returns are not affected by the variable requirements.

[15] In Panel B, we tabulate standardized estimates. Inferences are not changed when we use unstandardized estimates.

Overall, the results in this section support our claim that the negative association between asset growth and future returns can be explained by analyst forecast errors stemming from extrapolation bias. In other words, analyst forecast errors are indeed a mediator through which biased expectations about the implication of asset growth for future earnings are incorporated into stock returns.

5.6. Alternative Explanations

We examine two alternative explanations for our main findings. First, our finding of the positive association between optimistic forecast errors and asset growth might be driven by analysts' strategic behaviors rather than by extrapolation (e.g., Dugar and Nathan 1995). For example, it is possible that analysts strategically issue optimistic forecasts for high-growth firms to obtain better access to management's private information by pleasing them because high-growth firms are likely to have earnings that are more difficult to predict using public information. Alternatively, analysts may issue optimistic forecasts for high-growth firms to generate more investment banking business (e.g., underwriting of equity issuance) because growth firms are more likely to issue equity in the future. However, such strategic behaviors in which analysts aim to please management by initially issuing optimistic forecasts and then issuing pessimistic ones just before the earnings announcement are less likely to explain our findings because we do not find evidence of pessimistic forecasts for high-growth firms just before earnings announcements.

Nevertheless, to address this concern, we examine (1) whether the amount of equity financing affects the relation between analysts' optimism and growth and (2) whether our results are different between the pre- and post- Regulation Fair Disclosure (Reg FD) periods because Reg FD, which prohibits selective disclosure to analysts, reduces analysts' incentive to maintain good relationship with managers. The results (untabulated) suggest that analysts' optimism about asset growth does not change by equity financing or by the Reg FD. Therefore, it is unlikely that our results are driven by the analysts' incentive problems.

Second, one might argue that some of our empirical results are also consistent with the overinvestment explanation offered by Titman et al. (2004, 2009) that investors underreact to the value-destroying empire-building implications of increased investments by entrenched managers. In other words, if analysts were optimistic about the implications of overinvestment for future earnings, it would lead to the negative relation between asset growth and analyst forecast errors. In this case, analysts' biases arise from their failures to correctly assess the empire building behavior of managers, not from their extrapolation from past growth. To examine this possibility, we follow Titman et al. (2009) to decompose asset growth into the expected and unexpected asset growth components. We find that the coefficients on expected asset growth and unexpected growth are both negative and significant and that the magnitudes of these two coefficients are similar. This finding is not consistent with the overinvestment hypothesis that predicts that analyst forecast errors should be more strongly related to unexpected asset growth than expected asset growth. We thus conclude that the overinvestment hypothesis is unlikely the primary driver of our empirical results.

VI. CONCLUSIONS

In this study, we test the extrapolation hypothesis in explaining the asset growth anomaly by examining the relation between analysts' multi-period earnings forecasts and asset growth. We find that analyst forecasts are more optimistic for firms with high total asset growth. The optimism is more pronounced for long-term forecasts such as two- or three-year ahead earnings forecasts. The optimism is also higher for firms that have maintained similar levels of asset growth in recent periods, firms with higher information uncertainty, and forecasts with longer forecast horizons, all characterized by more likelihood of extrapolation. We also find that the growth effect in the stock market is substantially attenuated once analyst forecast errors are controlled for and that analyst long-term forecasts errors are an important mediator through which biased expectation about asset growth are incorporated into stock returns. These findings consistently support the extrapolation explanation for the asset growth anomaly and shed light on debates around the growth anomaly.

APPENDIX

Variable Definition

Variable	Definition
FE_{t+n}	$FE_{t+1,\ 1M}$, $FE_{t+1,\ 12M}$, $FE_{t+2,\ 1M}$, $FE_{t+2,\ 12M}$, $FE_{t+2,\ 24M}$, $FE_{t+3,\ 1M}$, $FE_{t+3,\ 12M}$, $FE_{t+3,\ 24M}$, $FE_{t+3,\ 36M}$, or $LTGFE_{\ 1M}$
$FE_{t+1(t+2,\ t+3),\ 1M\ (12M,\ 24M,\ 36M)}$	one- (two- and three-) year-ahead analyst forecast errors, computed as the realized annual EPS minus the corresponding consensus forecasts from the monthly IBES summary file in the first (12th, 24th, and 36th) month after the year *t* earnings announcement, all scaled by stock prices as of the end of the fiscal year;
$LTGFE_{1M}$	long-term earnings growth forecast errors, computed as the realized long-term earnings growth rate minus the corresponding monthly consensus forecasts from the monthly IBES summary file in the first month after the year *t* earnings announcement. Realized long-term earnings growth rate is the slope coefficient of a regression of the natural logarithm of annual EPS on a time trend using at least three EPS with a maximum of six (Bradshaw et al. 2006);
AG_t	asset growth defined as the change in total assets between year *t* and *t*-1, scaled by total assets of year *t*-1;
$WACC_t$	current accruals, computed as the change in working capital, scaled by lagged total assets;
$WCFO_t$	operating cash flows related to working capital, computed as operating income before depreciation and amortization minus the change in working capital, all scaled by lagged total assets;
$FE_{t,1M}$	prior analyst forecast errors, computed as the realized annual EPS for year *t* minus the corresponding consensus forecasts from the monthly IBES summary file in the first month after the year *t*-1 earnings announcement, all scaled by stock prices as of the end of the fiscal year *t*-1;
$LTGFE_{t,1M}$	prior long-term earnings growth forecast errors, computed as the realized long-term earnings growth rate minus the corresponding consensus forecasts from the monthly IBES summary file in the first month after the year *t*-1 earnings announcement. Realized long-term earnings growth rate is computed in a similar manner to $LTGFE_{1M}$;
$LOSS_t$	an indicator variable that takes the value of one if the firm reports a loss for the year, and zero otherwise;
$XFIN_t$	net external financing, measured as the sum of net debt issuance and net stock issuance, scaled by lagged total assets. The calculation of net debt issuance and net stock issuance is computed as described in Bradshaw et al. (2006);
$SIZE_t$	the natural log of the market value of equity at the end of the fiscal year;
BM_t	the ratio of book value of equity to market value of equity at the end of the fiscal year;
$CRET_t$	contemporaneous annual stock returns. The return cumulation begins three months after the beginning of the fiscal year;
RET_{t+1}	future monthly stock returns;

LEV_t	leverage, measured as the ratio of interest-bearing debt to total assets at the end of the fiscal year, and
MOM_t	annual stock returns in the latest fiscal year.

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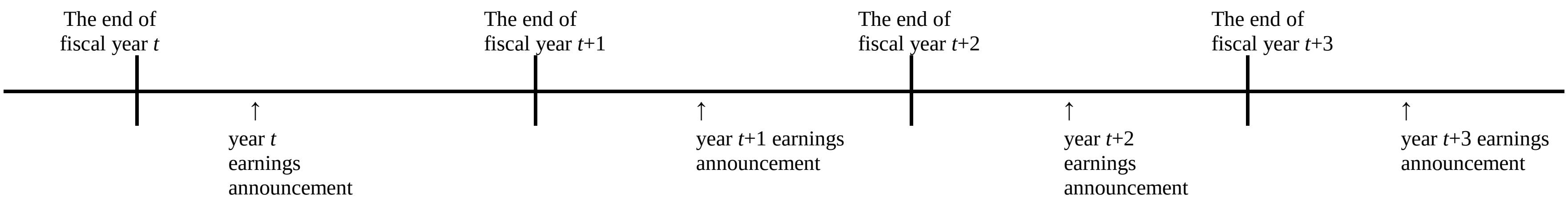
FIGURE 1A
The Time Line and Variables



Forecast period: *t*+1	$FE_{t+1,1M}$	…..	$FE_{t+1,12M}$				
Forecast period: *t*+2	$FE_{t+2,1M}$	…..	$FE_{t+2,12M}$	…..	$FE_{t+2,24M}$		
Forecast period: *t*+3	$FE_{t+3,1M}$	…..	$FE_{t+3,12M}$	…..	$FE_{t+3,24M}$	…..	$FE_{t+3,36M}$
Long-term earnings growth	$LGTFE_{1M}$	…..					

This figure illustrates the variable definitions of the analysts' forecasts errors for different periods at different points in time. We obtain consensus (mean) forecasts from the IBES summary files. IBES produces consensus earnings forecasts for each month on the Thursday before the third Friday of the month. $FE_{t+1,1M}$ ($FE_{t+1,12M}$) is the analysts' one-year-ahead forecast errors, calculated as the actual EPS for year *t*+1 minus the consensus (mean) forecasts from the monthly IBES summary file in the first (12^{th}) month after the announcement of year *t* earnings, scaled by stock prices as of the end of the fiscal year. $FE_{t+2,1M}$ ($FE_{t+2,12M}$, $FE_{t+2,24M}$) is the analysts' two-year-ahead forecast error, calculated as the actual EPS for year *t*+2 minus the corresponding consensus (mean) forecast from the monthly IBES summary file in the first (12^{th} and 24^{th}) month after the announcement of year *t* earnings, scaled by stock prices as of the end of the fiscal year. $FE_{t+3,1M}$ ($FE_{t+3,12M}$, $FE_{t+3,24M}$, $FE_{t+3,36M}$) is the analysts' three-year-ahead forecast error, calculated as the actual EPS for year *t*+3 minus the corresponding consensus (mean) forecast from the IBES summary file in the first (12^{th}, 24^{th}, and 36^{th}) month after the announcement of year *t* earnings, scaled by stock prices as of the end of the fiscal year.

FIGURE 1B
The Time Line and Variables –An Example

Fiscal year end:	Dec 31, 2008		Dec 31, 2009		Dec 31, 2010		Dec 31, 2011
Earnings announcement date	Feb 5, 2009		Feb 5, 2010		Feb 5, 2011		Feb 5, 2012
From IBES monthly summary file on	Feb 15, 2009		Jan 14, 2010		Jan 20, 2011		Jan 19, 2012
Forecast period: Dec 31, 2009	$FE_{t+1,1M}$	…..	$FE_{t+1,12M}$				
Forecast period: Dec 31, 2010	$FE_{t+2,1M}$	…..	$FE_{t+2,12M}$	…..	$FE_{t+2,24M}$		
Forecast period: Dec 31, 2011	$FE_{t+3,1M}$	…..	$FE_{t+3,12M}$	…..	$FE_{t+3,24M}$	…..	$FE_{t+3,36M}$
Long-term earnings growth	$LTTGFE_{1M}$	…..					

This figure illustrates a case in which a firm has a December fiscal year and announces annual earnings on the following 5th of February, every year.

TABLE 1
Descriptive Statistics

Variables	N	Mean	Std. Dev.	1st quartile	Median	3rd quartile
$FE_{t+1,\ 1M}$	61,943	-0.032	0.120	-0.030	-0.004	0.005
$FE_{t+1,\ 12M}$	51,119	-0.005	0.035	-0.002	0.000	0.003
$FE_{t+2,\ 1M}$	43,689	-0.033	0.113	-0.048	-0.011	0.006
$FE_{t+2,\ 12M}$	51,609	-0.024	0.089	-0.030	-0.005	0.006
$FE_{t+2,\ 24M}$	42,977	-0.004	0.028	-0.002	0.000	0.003
$FE_{t+3,\ 1M}$	13,134	-0.029	0.104	-0.051	-0.013	0.008
$FE_{t+3,\ 12M}$	31,293	-0.031	0.103	-0.047	-0.011	0.007
$FE_{t+3,\ 24M}$	44,471	-0.022	0.083	-0.029	-0.005	0.007
$FE_{t+3,\ 36M}$	36,805	-0.003	0.025	-0.002	0.000	0.003
$LTGFE_{1M}$	38,014	-0.101	0.248	-0.210	-0.066	0.029
AG_t	70,123	0.166	0.405	-0.017	0.075	0.218
$WACC_t$	70,123	0.020	0.077	-0.015	0.009	0.044
$WCFO_t$	70,123	0.098	0.184	0.044	0.119	0.190
$FE_{t,\ 1M}$	70,123	-0.029	0.110	-0.030	-0.004	0.006
$LTGFE_{t,\ 1M}$	42,430	-0.107	0.252	-0.220	-0.070	0.028
$LOSS_t$	70,123	0.273	0.445	0.000	0.000	1.000
$XFIN_t$	70,123	0.069	0.275	-0.044	0.000	0.063
$SIZE_t$	70,123	6.065	1.989	4.625	5.949	7.361
BM_t	70,123	0.606	0.486	0.290	0.486	0.758
$CRET_t$	70,123	0.154	0.654	-0.236	0.054	0.368

This table reports the descriptive statistics of one- (two-and three-) year-ahead forecast errors ($FE_{t+1(t+2,\ t+3),1M\ (12M,\ 24M,\ 36M)}$), long-term earnings growth forecast errors ($LTGFE_{1M}$), asset growth (AG_t), and the control variables in the regression analyses. See appendix for variable definitions.

TABLE 2
Correlations

Variables	$FE_{t+1,1M}$	$FE_{t+2,1M}$	$FE_{t+3,1M}$	$LTGFE_{1M}$	AG_t	$WACC_t$	$WCFO_t$	$LOSS_t$	$XFIN_t$	$SIZE_t$	BM_t	$CRET_t$
$FE_{t,1M}$	0.42	0.31	0.18	-0.13	0.13	0.11	0.21	-0.36	-0.02	0.29	-0.24	0.17
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
$FE_{t+1,1M}$		0.57	0.34	0.07	0.02	-0.04	0.14	-0.17	-0.05	0.23	-0.22	0.16
		(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
$FE_{t+2,1M}$			0.65	0.27	-0.04	-0.06	0.12	-0.12	-0.08	0.20	-0.13	0.08
			(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
$FE_{t+3,1M}$				0.42	-0.08	-0.06	0.18	-0.14	-0.15	0.19	-0.03	0.03
				(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(0.00)	(0.00)
$LTGFE_{1M}$					-0.17	-0.15	-0.09	0.13	-0.11	0.05	0.13	-0.01
					(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(0.01)
AG_t						0.23	0.08	-0.13	0.74	0.08	-0.20	0.14
						(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
$WACC_t$							-0.25	-0.15	0.18	-0.06	-0.08	0.00
							(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(0.36)
$WCFO_t$								-0.54	-0.35	0.32	-0.11	0.14
								(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
$LOSS_t$									0.19	-0.32	0.18	-0.14
									(<.001)	(<.001)	(<.001)	(<.001)
$XFIN_t$										-0.10	-0.12	0.04
										(<.001)	(<.001)	(<.001)
$SIZE_t$											-0.38	0.13
											(<.001)	(<.001)
BM_t												-0.27
												(<.001)

This table presents the Pearson correlation coefficients. The significance of the correlation is presented in parentheses. See appendix for variable definitions.

TABLE 3
The Effect of Asset Growth on Analyst Forecast Errors

Dependent variable =	(1) $FE_{t+1, 1M}$	(2) $FE_{t+2, 1M}$	(3) $FE_{t+3, 1M}$	(4) $LTGFE_{1M}$
Intercept	-0.052 ***	-0.110 ***	-0.145 ***	-0.039*
	(-4.09)	(-6.74)	(-8.10)	(-1.82)
AG_t	-0.009 ***	-0.019 ***	-0.020 ***	-0.035***
	(-3.94)	(-6.42)	(-3.71)	(-7.16)
$WACC_t$	-0.096 ***	-0.060 ***	-0.036 *	-0.190***
	(-11.41)	(-5.53)	(-1.73)	(-9.50)
$WCFO_t$	-0.004	0.020 ***	0.067 ***	-0.112***
	(-0.86)	(3.04)	(5.80)	(-8.77)
$FE_{t, 1M}$ or $LTGFE_{t, 1M}$	0.458 ***	0.371 ***	0.192 ***	0.766***
	(22.81)	(13.41)	(5.75)	(131.06)
$LOSS_t$	-0.004 **	0.001	-0.001	0.045***
	(-2.28)	(0.30)	(-0.31)	(11.20)
$XFIN_t$	-0.003	0.004	0.004	0.018**
	(-0.82)	(0.92)	(0.47)	(2.24)
$SIZE_t$	0.006 ***	0.007 ***	0.007 ***	0.002***
	(19.14)	(16.86)	(8.86)	(2.61)
BM_t	-0.029 ***	-0.015 ***	0.004	0.037***
	(-12.42)	(-4.59)	(0.68)	(9.11)
$CRET_t$	0.014 ***	0.006 ***	0.006 ***	-0.053***
	(15.09)	(6.15)	(3.22)	(-24.61)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.230	0.151	0.121	0.582
N	61,943	43,689	13,134	35,065

Test of difference between the coefficients on AG_t

	χ^2	p-value
$FE_{t+2, 1M} = FE_{t+1, 1M}$	13.13	0.00
$FE_{t+3, 1M} = FE_{t+1, 1M}$	5.75	0.02
$LTGE_{1M} = FE_{t+1, M}$	18.68	0.00

This table reports the results of regressing analyst forecast errors on asset growth. *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively, in two-tailed tests. All of the t-statistics (in parentheses) are based on standard errors clustered by firm. See appendix for variable definitions.

TABLE 4
Reversals of Asset Growth and Analyst Forecast Errors

Panel A: Subsample of Firms without Reversals of Asset Growth

Dependent variable =	(1) $FE_{t+1, 1M}$	(2) $FE_{t+2, 1M}$	(3) $FE_{t+3, 1M}$	(4) $LTGFE_{1M}$
AG_t	-0.009 ***	-0.019 ***	-0.021 ***	-0.038***
	(-3.57)	(-5.84)	(-3.58)	(-6.99)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.235	0.152	0.133	0.592
N	53,643	38,151	11,543	31,934

Panel B: Subsample of Firms with Reversals of Asset Growth

Dependent variable =	(1) $FE_{t+1, 1M}$	(2) $FE_{t+2, 1M}$	(3) $FE_{t+3, 1M}$	(4) $LTGFE_{1M}$
AG_t	-0.007	-0.017 **	-0.016	-0.018*
	(-1.26)	(-2.51)	(-1.26)	(-1.66)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.213	0.149	0.103	0.501
N	8,300	5,538	1,591	3,131
Difference of the coefficient on AG_t between two groups	-0.002	-0.008	-0.005	-0.020 **
z-statistics	[0.34]	[0.30]	[0.43]	[1.65]
p-value	0.367	0.384	0.332	0.048

This table reports the results of regressing analyst forecast errors on asset growth for the subsamples of firms without reversals of asset growth (Panel A) and with reversals of asset growth (Panel B). Firms with reversals of asset growth are those whose current asset growth is in the highest (lowest) 30% and whose past three-year-average asset growth is in the lowest (highest) 30%. *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively, in two-tailed tests. All of the *t*-statistics (in parentheses) are based on standard errors clustered by firm. The control variables are included in the estimation but not reported here. We follow Clogg et al. (1995) to test the significance of the reduction in the coefficients on *AG* between Panel A and B. See appendix for variable definitions.

TABLE 5
The Effect of Information Uncertainty on the Relation between Asset Growth and Analyst Forecast Errors

Panel A: Low Information Uncertainty Group

Dependent variable =	(1) $FE_{t+1, 1M}$	(2) $FE_{t+2, 1M}$	(3) $FE_{t+3, 1M}$	(4) $LTGFE_{1M}$
AG_t	-0.002	-0.013***	-0.010*	-0.030***
	(-0.70)	(-3.05)	(-1.78)	(-4.40)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.172	0.100	0.048	0.596
N	20,460	16,642	5,377	14,109

Panel B: High Information Uncertainty Group

Dependent variable =	(1) $FE_{t+1, 1M}$	(2) $FE_{t+2, 1M}$	(3) $FE_{t+3, 1M}$	(4) $LTGFE_{1M}$
AG_t	-0.010 ***	-0.021***	-0.025*	-0.049***
	(-3.05)	(-4.93)	(-3.08)	(-6.43)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.188	0.116	0.068	0.556
N	21,799	17,711	5,584	14,226
Difference of the coefficient on AG_t between two groups	0.008**	0.008*	0.015*	0.019**
z-statistics	[1.65]	[1.25]	[1.58]	[1.83]
p-value	0.050	0.100	0.057	0.033

This table reports the results of regressing analyst forecast errors on asset growth for the subsample of firms having low and high information uncertainty. We use firm size, age, return volatility, cash flow volatility, and VIX as proxies of information uncertainty. For each information uncertainty proxy and fiscal year, we construct the indicator variable equal to one for firms with high information uncertainty, zero otherwise. If the average value of five information uncertainty indicator variables is higher than 0.5, the observation is classified as a high information uncertainty group. *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively, in two-tailed tests. All of the *t*-statistics (in parentheses) are based on standard errors clustered by firm. The control variables are included in the estimation but not reported here. We follow Clogg et al. (1995) to test the significance of the reduction in the coefficients on *AG* between Panel A and B. See appendix for variable definitions.

TABLE 6

The Effect of Asset Growth on Analyst Forecast Errors measured at Different Points in Time

Dependent variable =	One-year-ahead earnings forecast		Two-year-ahead earnings forecast			Three-year-ahead earnings forecast			
	(1) $FE_{t+1,\,1M}$	(2) $FE_{t+1,\,12M}$	(3) $FE_{t+2,\,1M}$	(4) $FE_{t+2,\,12M}$	(5) $FE_{t+2,\,24M}$	(6) $FE_{t+3,\,1M}$	(7) $FE_{t+3,\,12M}$	(8) $FE_{t+3,\,24M}$	(9) $FE_{t+3,\,36M}$
Intercept	-0.052 ***	-0.011 ***	-0.110 ***	-0.077 ***	-0.018 ***	-0.145 ***	-0.101 ***	-0.069 ***	-0.013 ***
	(-4.09)	(-3.64)	(-6.74)	(-5.24)	(-3.59)	(-8.10)	(-8.00)	(-5.12)	(-3.66)
AG_t	-0.009 ***	-0.002	-0.019 ***	-0.011 ***	-0.003 ***	-0.020 ***	-0.012 ***	-0.005 **	-0.003 ***
	(-3.94)	(-1.62)	(-6.42)	(-5.14)	(-3.52)	(-3.71)	(-3.78)	(-2.37)	(-3.84)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.230	0.104	0.151	0.129	0.069	0.121	0.116	0.105	0.046
N	61,943	51,119	43,689	51,609	42,977	13,134	31,293	44,471	36,805

Test of difference between the coefficients on AG_t

	χ^2	*p*-value
$FE_{t+2,\,1M} = FE_{t+1,\,1M}$	13.13	0.00
$FE_{t+3,\,1M} = FE_{t+1,\,1M}$	5.75	0.02
$FE_{t+2,\,12M} = FE_{t+1,\,12M}$	32.96	0.00
$FE_{t+3,\,12M} = FE_{t+1,\,12M}$	17.93	0.00
$FE_{t+1,\,1M} = FE_{t+1,\,12M}$	62.75	0.00
$FE_{t+2,\,1M} = FE_{t+2,\,12M}$	53.14	0.00
$FE_{t+2,\,12M} = FE_{t+2,\,24M}$	32.88	0.00
$FE_{t+3,\,1M} = FE_{t+3,\,12M}$	11.66	0.00
$FE_{t+3,\,12M} = FE_{t+3,\,24M}$	14.61	0.00
$FE_{t+3,\,24M} = FE_{t+3,\,36M}$	1.11	0.29

This table reports the results of regressing analyst forecast errors measured at different points in time on asset growth. *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively, in two-tailed tests. All of the *t*-statistics (in parentheses) are based on standard errors clustered by firm. The control variables are included in the estimation but not reported here. See appendix for variable definitions.

TABLE 7
Future Stock Returns, Asset Growth, and Analyst Forecast Errors

Panel A. Fama-Macbeth Estimation

	Dependent variable= Monthly stock returns				
	(1) Baseline	(2) *FE* = $FE_{t+1, 1M}$	(3) *FE* = $FE_{t+2, 1M}$	(4) *FE* = $FE_{t+3, 1M}$	(5) *FE* = $LTGFE_{1M}$
Intercept	2.532 ***	2.842 ***	3.068 ***	2.657 ***	3.183 ***
	(4.50)	(5.11)	(5.33)	(3.91)	(5.83)
AG_t	-0.400 ***	-0.292 **	-0.135	-0.189	-0.100
	(-2.80)	(-2.07)	(-0.95)	(-0.97)	(-1.08)
FE		19.442 ***	18.640 ***	11.146 ***	2.874 ***
		(17.50)	(21.11)	(10.39)	(17.63)
$SIZE_t$	-0.172 ***	-0.216 ***	-0.228 ***	-0.159 ***	-0.206 ***
	(-3.76)	(-4.82)	(-5.03)	(-2.91)	(-4.55)
LEV_t	-0.615	-0.457	-0.427	-0.775 *	-0.919 ***
	(-1.61)	(-1.20)	(-1.09)	(-1.74)	(-2.46)
BM_t	0.174	0.414 ***	0.372 **	0.493 *	-0.043
	(1.21)	(2.91)	(2.45)	(1.67)	(0.30)
MOM	-0.177	-0.320 **	-0.251 *	0.054	-0.180
	(-1.33)	(-2.48)	(-1.86)	(0.26)	(-1.36)
Average R^2	0.036	0.049	0.055	0.098	0.042
N	273	273	273	273	273
% Reduction in the *AG* coefficient		27%	66% *	53%	75% **
z-statistics		[0.54]	[1.31]	[1.26]	[2.10]
p-value		0.295	0.095	0.103	0.018

Panel B. Mediation Effect - Path Analysis:
The Effect of Forecast Errors on the Relation between Asset Growth and Future Stock Returns

	(1) $FE = FE_{t+1, 1M}$		(2) $FE = FE_{t+2, 1M}$		(3) $FE = FE_{t+3, 1M}$		(4) $FE = LTGFE_{1M}$	
	Coefficient	*z*-stat	Coefficient	*z*-stat	Coefficient	*z*-stat	Coefficient	*z*-stat
Total effect								
[*AG* → *Ret*]	-0.021***	-10.50	-0.020***	-9.13	-0.028***	6.96	-0.021***	-10.50
Percentage	100%		100%		100%		100%	
Direct effect								
[*AG* → *Ret*]	-0.021***	-10.59	-0.014***	-6.78	-0.022***	-5.66	-0.012***	-7.52
Percentage	98%		73%		78%		55%	
Indirect effect								
[*AG* →*FE*]	-0.006	-1.06	-0.057***	-7.39	-0.071***	-5.83	-0.174***	-117.59
[*FE* → *Ret*]	0.068***	19.65	0.098***	31.75	0.083***	15.58	0.053***	34.20
Total indirect effect	0.000	-1.05	-0.006***	-6.90	-0.006***	-5.50	-0.009***	-20.55
Percentage	2%		29%		21%		44%	

Panel A of this table reports the Fama-Macbeth estimation results of regressing future monthly returns on asset growth, analyst forecast errors, and control variables. We use monthly returns from April 1989 to December 2011, which corresponds to 273 months. The number of firm-month observations used in the regression is 421,645 for Columns (1) and (2), and 358,898, 113,529, and 421,645 observations for Columns (3), (4), and (5), respectively. The independent variables in year *t* are matched to the monthly returns for the 12-month period beginning in the fourth month of the year *t+1*. Based on Clogg et al. (1995), % Reduction in the *AG* coefficient" calculates the extent that an inclusion of the forecast error variable reduces the coefficient on *AG* compared to that reported in Column (1). Panel B of this table reports the standardized estimates of path analysis of the effect of analyst forecast errors on the relation between asset growth and future monthly stock returns. We use the forecast error variables ($FE_{t+1, 1M}$, $FE_{t+2, 1M}$, $FE_{t+3, 1M}$, and $LTGFE_{1M}$) as mediating variables. We use monthly returns from April 1989 to December 2011. The number of firm-month observations used in the regression is 421,645 for Columns (1) and (2), and 358,898, 113,529, and 421,645 observations for Columns (3), (4), and (5), respectively. The independent variables in year *t* are matched to the monthly returns for the 12-month period beginning in the fourth month of the year *t*+1. [*A* → *B*] is the coefficients on independent variable, *A*, in the regression of dependent variable, *B*. "Total indirect effect" is the product of (i) the coefficient on asset growth in the forecast error regression and (ii) the coefficient on the forecast error variable in the future return regression (see Preacher et al. 2007). *Percentage* is the ratio of direct or indirect effect on total effect. All of the *z*-statistics (in parentheses) are based on standard errors clustered by firm. *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively, in two-tailed tests. See appendix for variable definitions.