

Analyst Incentives, Forecast Biases, and Stock Returns:

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Abstract:

Prior studies suggest that analysts have incentives to bias their earnings forecasts, especially for longer horizon forecasts. We use the difference between analysts' two-year and one-year-ahead earnings forecasts (FECH) as a measure of analysts' biased incentives. We find that high FECH firms underperform low FECH firms by 0.85% in the following month and the underperformance persists up to at least six months. In addition, the negative FECH-return relation is more pronounced when analyst incentives to bias forecasts are higher. Finally, high FECH firms have significantly negative future forecast errors and forecast revisions when their incentives to bias forecasts are high. Overall, our study indicates that analyst incentives to bias forecasts have implications for stock market efficiency.

JEL Classification: G14; G29; M4

Keywords: Sell-side analysts; forecast incentives; market efficiency

Data Availability: Data are available from the public sources identified in the paper.

1. Introduction

The accounting and finance literature regard financial analysts as important information intermediaries in the market (see Healy and Palepu (2001) for a review). For example, analysts are sophisticated financial professionals who produce future earnings forecasts to investors and help them make investment decisions (e.g., Barth and Hutton (2000)). Such a view, however, has been recently challenged by several studies. For example, Bradshaw et al. (2012) document that analyst earnings forecasts, in particular those with long forecast horizons, are even less accurate than simple random walk time-series forecasts. Relatedly, Altinkilic and Hansen (2009) and Altinkilic, Balashov and Hansen (2013) show that the revisions of analyst recommendations and analyst earnings forecasts release little new information to the market and contend that the prior literature may have overstated analysts' role as information agents. In this paper, we contribute to the debate by examining whether analyst incentives to biased forecast jeopardize their role as information intermediaries and are associated with mispriced stocks.

To capture analyst incentives to bias their forecasts, we follow the findings of Bradshaw et al. (2012) that analysts' forecasts of 1-year-ahead earnings (FY1) in lieu of analysts' forecasts of 2-year-ahead earnings (FY2) often yields more accurate forecasts of future 2-year-ahead actual earnings. In particular, following prior studies on analysts' incentives to bias forecasts, we conjecture that analysts' economic forecast incentives drive the more biased longer horizon (FY2) forecasts. First, analysts have little incentive to collect additional information beyond what is necessary for FY1 forecasts when forecasting longer horizon earnings. Although prior research show that analysts enjoy some career benefits from more accurate earnings forecasts (e.g., Hong and Kubik (2003); Emery and Li (2009); Leone and Wu

(2002)), the assessment of forecast accuracy is mostly based on their near-term forecasts rather than longer-term forecasts such as FY2. The lack of economic benefits associated with more accurate forecasts together with the greater difficulty in forecasting longer-term earnings (e.g., Chan, Karceski, and Lakonishok (2003)) suggests that analysts would exert little additional effort to forecasts FY2. Consequently, the adjustments that analysts make upon their FY1 forecasts to forecasts two-year-ahead earnings, or the difference between FY2 and FY1 forecasts (FECH hereafter), unlikely contain much information.

Second, prior research shows that analysts have incentives to issue intentionally optimistic forecasts for reasons such as generating more trading commissions, trading bias for information, and obtaining investment banking business (see, for example, Francis and Philbrick (1993); Hayes (1998); Lim (2001); Michaely and Womack (1999); and Bradshaw and Jackson (2005); Richardson and Sloan (2006)). Intentional forecast optimism resulting from biased incentives should be more pronounced for FY2 than for FY1, as optimistic FY1 will be more difficult for companies to meet or beat. In addition, optimistic FY1 will lead to lower forecast accuracy and therefore may jeopardize analysts' reputation, compensation, and career advancement. The costs of inaccuracy resulting from intentional bias are less of a concern for FY2 forecasts, as there will be plenty of time for analysts to revise down their forecasts so that companies can beat or meet. Moreover, as discussed above, analysts themselves are not particularly concerned about the bias in FY2 forecasts either since they are rarely evaluated based on longer horizon forecasts such as FY2. Hence, we use FECH as an empirical measure for analyst incentives to bias forecasts.

To validate that FECH are largely driven by analyst biased forecast incentives, we first show that FECH is mildly associated with future actual earnings. Future actual earnings

changes explain about 7% of the cross-sectional variation in FECH. Second, analyst biased economic incentives play a significant role in determining FECH (and hence FY2 forecasts). We document that FECH is significantly associated with proxies of analyst biased forecast incentives such as the needs of firms' external financing, commission generation opportunities, and information uncertainty of the followed firms. Collectively, proxies of analyst biased economic incentives increase the adjusted R-squared of the FECH regression to approximately 26%. Third, consistent with the notion that high FECH reflects analyst biased forecast incentives, we document that high FECH firms are associated with significantly lower FY1 and FY2 forecast errors and lower future revisions of earnings forecasts and growth forecasts over the subsequent periods.

We then examine whether analyst incentives to bias forecasts lead to mispriced equities. Specifically, we investigate whether the stock market fully understands the predictable optimistic bias associated with high FECH firms. If investors fail to fully appreciate the biased forecast incentives, they will be surprised by the future predictable downward revisions and negative forecast errors associated with higher FECH firms. Our results show that stocks in the highest FECH decile earn a negative risk-adjusted return of around -0.92 to -1.15% over the following month. A hedge portfolio that buys stocks with the lowest FECH and shorts stocks with the highest FECH also generates significant hedge returns of approximately 0.85% per month. The predictive power of FECH over future stock returns persists up to at least six months after portfolio formation and remains statistically significant even after controlling other known return predictors such as accruals, earnings surprises, and growth forecast disparity.

We also conduct several additional analyses. First, our tests suggest that the results are stronger among firms followed by analysts with greater incentives to bias forecasts. For example, we find higher abnormal returns to the FECH strategy among firms with greater needs for external financing, firms with greater commission generation potentials, and firms with greater information uncertainty. Second, we show that analyst extrapolation of past growth unlikely explains our results. Our tests show that past sales and earnings growth are negatively associated with FECH after controlling for the information components and other determinants of FECH. Furthermore, controlling for past earnings and sales growth has little impact on the performance of the FECH-based trading strategies. Third, consistent with FECH reflecting mispricing, we show that FECH-based trading strategy performs better among firms with high idiosyncratic volatility and when investor sentiment is high. Finally, we show that FECH strategy generates significant returns in both the early and recent subsample periods and the abnormal returns are robust to alternative risk models of Chen, Novy-Marx, and Zhang (2011) and Novy-Marx (2012).

This paper contributes to the existing literature in three ways. First, our study shades lights on the debate of analysts' role as information intermediaries. Prior literature on the role of financial analysts in capital markets, on one hand, indicates that analysts play a valuable role in improving market efficiency. For example, Barth and Hutton (2000) find that stock prices for firms with higher analyst following more rapidly incorporate information on accruals and cash flows than prices of less followed firms. However, on the other hand, analysts themselves also receive pressure from a variety of sources that could affect their incentives and reduce their role as information intermediaries. For example, analysts are pressured by their employers to secure more investment banking business and are also pressured by peer competition to maintain a

good relationship with firm managers to gain access to private information. Our findings that analyst biased forecast incentives can lead to mispriced equities suggest that the role of analysts in improving market efficiency may be overstated.

Second, our empirical finding of the negative relation between FECH and future returns provides insights to detect analysts' incentives to bias forecasts. The fact that forecast bias cannot be detected *ex ante* provides difficulty to undo the biased forecasts. Our findings provide a simple measure that effectively captures forecast bias by taking advantage of the concurrent multiple forecasts, and it turns out to be a powerful predictor of future forecast errors, forecast revisions and stock returns. Our study thus contributes to the better understanding of analyst behavior and provides an easy way to identify and adjust analyst optimistic bias before the realization of actual earnings.

Third, although it seems common that analysts issue multiple forecasts with different horizons concurrently, our empirical evidence suggests that investors do not fully recognize more optimistic bias in the longer horizon analyst forecasts. By using these concurrent forecasts, we can form arbitrage strategies. Specifically, simply taking the difference of two-year ahead and one-year ahead EPS forecasts as our proxy of analyst biased incentives, we are able to formulate a trading strategy with annualized alpha of those stocks amounts to about 7.4-9.7%. Our study thus contributes to exploring the opportunities to identify potential arbitrage opportunities based on the analyst biased incentives.

The remainder of the paper is organized as follows. Section 2 reviews the related literature and develops our hypotheses. Section 3 develops the research question and outlines the research designs. Section 4 presents the data and sample selection procedures. Section 5 reports and discusses the empirical results. Section 6 concludes.

2. Related Literature and Hypothesis Development

Analysts' earnings per share (EPS) forecasts provide an important source of information for investors to make investment decisions. Existing literature shows that the market reacts strongly to analysts' forecast revisions and the strength of the reaction varies with analysts' characteristics such as reputation, past forecast accuracy, and media coverage (e.g., Fried and Givoly (1982); Imhoff and Lobo (1984); Lys and Sohn (1990); Stickel (1991); Park and Stice (2000); Gleason and Lee (2003); Clement and Tse (2003)). The significant market reaction to analysts' forecast revisions, to certain extent, reflects the common practice of using analysts' forecasts as surrogates for future earnings in equity valuations. For example, Kim and Ritter (1999) show that P/E multiples using forecasted earnings result in more accurate valuations than multiples using trailing earnings for valuing initial public offerings. In a more general setting, Liu et al. (2002; 2007) find that forward earnings have the best explanatory power over stock prices among a comprehensive list of value drivers such as the book value of equity, trailing earnings, and cash flows.

Investors use the multiple periods of forecasts to formulate the valuation of the underlying securities. For example, the implementation of more sophisticated valuation models such as the residual income model (Ohlson (1995); Feltham and Ohlson (1995)) often involves exacting future residual incomes from analysts' earnings forecasts. Analysts usually provide explicit EPS forecasts for up to two years. In order to estimate longer horizon residual incomes and the terminal values, researchers often extrapolate FY2 forecasts and long-term growth forecasts (e.g., Frankel and Lee (1998); Lee et al. (1999); Easton et al. (2002)). Consequently, FY2 have considerable impact on the estimates of intrinsic value. If investors adopt similar techniques, FY2 will affect stock prices as well (Liu and Thomas (2000); Begley and Feltham

(2002)). Indeed, Cheng (2005) shows that analysts' two-year-ahead EPS forecasts have significant explanatory power over the market-to-book equity ratio even after controlling one-year-ahead EPS forecasts, analysts' long-term growth forecasts, and a comprehensive list of other determinants.

Even though analysts' longer horizon earnings forecasts are important inputs for equity valuation, the properties of these forecasts are not well-known as most of the existing research focuses on short-term EPS forecasts ranging from one quarter to one-year-ahead of earnings announcements (see Ramnath et al. (2008) for a survey). A recent study by Bradshaw et al. (2012) compares the accuracy of simple random walk time-series forecasts to that of analyst forecasts at various horizons. They find that while analysts' FY1 forecasts are always superior to the random walk time-series forecasts, analysts' longer horizon forecasts such as FY2 and FY3 are often less accurate than the random walk forecasts. Furthermore, they also document that using analysts' forecasts of 1-year-ahead earnings (FY1) in lieu of analysts' forecasts of 2-year-ahead earnings (FY2) yields more accurate forecasts of future 2-year-ahead actual earnings over most of the forecast horizons.

If analysts' objective is to provide the most accurate forecasts, one would expect that FY2 forecasts should be at least as accurate or informative as FY1 as forecasts. One possible reason for the apparent inability of analysts to utilize their own FY1 forecasts to come up with more accurate forecasts of two-year-ahead earnings is that analysts suffer from severe cognitive biases, which prevent them from processing their own information efficiently. Given that sell-side analysts are sophisticated financial professionals, it is unlikely that they are naïve even with respect to their own short-term forecasts. However, this does raise the questions why

analysts do not simply use their FY1 forecasts as forecasts for two-year-ahead earnings. In other words, what is in the difference between analysts' FY1 and FY2 forecasts?

We posit analysts' biased forecast incentives play an important role in determining the difference between FY1 and FY2 forecasts. Prior literature shows that analysts have incentives to issue overly optimistic forecasts and recommendations for various reasons. Optimistic bias arising from biased forecast incentives should be more pronounced for longer horizon forecasts such as FY2 than shorter horizon forecasts such as FY1.

First, a cost that analysts have to bear for intentional optimistic biased forecasts is that their reputation and compensation may suffer from the resulting low forecast accuracy (Stickel (1992); Mikhail et al. (1999); Hong et al. (2000); Bradshaw and Brown (2006)). Such cost is lower for biased FY2 forecasts because analysts are rarely assessed by the accuracy of their longer horizon forecasts. Second, analysts' earnings forecasts are important benchmarks that managers want to meet (e.g., Brown (2003); Brown and Caylor (2005); Graham et al. (2005)). Prior studies suggest that missing analysts' forecasts, even by a penny, may lead to severe market punishments (Skinner and Sloan (2002)), while beating or meeting expectations is rewarded with market premiums (Bartov, Givoly, and Hayn (2002)). Optimistic FY1 forecasts are difficult for companies to meet, which may not be desirable from managers' perspective. In contrast, optimistic FY2 forecasts present no problems for managers since there will be plenty of time for analysts to revise them down.¹ Due to these reasons, we predict that the change in analysts' forecasts of future earnings between one-year ahead and two-year ahead (i.e., FY2-

¹ Consistent with these predictions, prior literature documents that companies tend to walk down optimistic long horizon forecasts to beatable levels before earnings announcements (e.g. Richardson et al. 2004; Cotter et al. 2006; Ke and Yu 2006). Our research differs from these paper in an important way: they only compare the bias of FY1 forecasts issued at *different point in time* with different forecast horizons, while we compare the bias/accuracy of FY2 and FY1 forecasts issued *concurrently* both as forecasts for two-year ahead earnings.

FY1) is significantly affected by their biased forecast incentives. We examine the following incentives proposed by the literature.

2.1 Investment banking business incentives

Many analysts are employed by investment banks, for which underwriting business is an important source of revenues for the banks. The underwriting relationships create a potential conflict of interests for analysts. Lin and McNichols (1998) demonstrate that long-term growth forecasts and recommendations made by affiliated underwriting analysts are more optimistic than those by non-affiliated analysts. Similar optimism in recommendations and long-term earnings growth forecasts around equity offerings is documented by Michaely and Womack (1999) and Dechow et al. (2000), respectively. Without distinguishing between affiliated and unaffiliated analysts, Bradshaw et al. (2006) find that firms with a higher level of external financing are associated with greater overoptimism in analysts' forecasts. Competition for investment banking business gives analysts' incentives to issue intentionally optimistic forecasts. Following Frank and Goyal (2003) and Kadan, Madureira, Wang, and Zach (2009), we argue that firms with greater financing deficits (i.e., those with larger negative free cash flows and those with greater financial constraints) tend to have greater potentials for investment banking business. We measure free cash flow (FCF) as the sum of cash flow from operating activities and cash flow from investing activities scaled by average total assets. We measure financial constraints (FC) following Kaplan and Zingales (1997), with the detailed definition provided in the Appendix.

2.2 Trading commission generation incentives

Trading commission is another source of revenues for brokerage firms for which many analysts work. According to Cowen et al. (2006), analysts' compensation is typically linked to

commissions and soft-dollar revenues in the stocks they cover, which therefore motivates analysts to provide optimistic research to encourage investors to trade stocks. They find that analysts employed by brokerage firms make more optimistic forecasts than those employed by firms with underwriting services, suggesting that trading incentives are important factors underlying analyst optimism. Along the same lines, Jackson (2005) also argues that trading incentives generate analyst optimism. Analysts should be able to generate more trading business and commissions for firms with larger trading volume, and for those with greater investor visibility/recognitions. We use the logarithm of the trading volume (in million dollars) as proxy for trading volume (VOLUME), and the ownership breadth measure developed by Lehavy and Sloan (2008) as a proxy for investor recognition (IREC). Because both measures are highly correlated with firm size, we further adjust them for firm size by ranking them into deciles within the monthly size deciles and then standardize them into a range of between 0 and 1.

2.3 *Obtaining managerial information incentives*

Information disclosure by management is an important source of information for analysts. Prior to the adoption of Regulation Fair Disclosure (REG FD), managers may disclose their private information selectively to analysts who hold optimistic views on their companies (e.g., Chen and Matsumoto (2006)). In the post-REG FD era, Mayew (2008) finds that managers still discriminate among analysts by granting more favorable analysts more participation in asking questions during conference calls. Analysts, in order to obtain better information from managers, therefore have incentives to issue optimistic forecasts to maintain a good relationship with management (e.g., Francis and Philbrick (1993); Das et al. (1998); Lim (2001)). We predict that such incentives also impact FY2 forecasts more than FY1, which

therefore influences analysts' forecasts of earnings changes. Indeed, Ke and Yu (2006) find that analysts who issue initial optimistic earnings forecasts followed by pessimistic earnings forecasts before the earnings announcement produce more accurate earnings forecasts and are less likely to be fired by their employers. We argue that incentives to issue optimistic longer horizon forecasts to obtain better information from managers should be stronger for firms with hard-to-predict earnings or higher information uncertainty (Ke and Yu (2006)). We use earnings volatility (EVOL), return volatility (RVOL), and firm size (SIZE) to proxy for such incentive. To summarize, our first set of hypothesis are as follows:

Hypothesis 1: Analysts' forecasts of earnings changes (FECH) are positively associated with their incentives to obtain investment banking business, the incentive to generate trading commission, and the incentive to obtain managerial information disclosures, after controlling for future actual earnings changes.

Presumably, the difference between analysts' FY2 and FY1 forecasts should also reflect analysts' projections of future earnings changes. However, analysts have little incentive to collect additional information beyond what is necessary for FY1 forecasts when forecasting longer horizon earnings. The career benefits associated with more accurate earnings forecasts as documented in the prior literature (e.g., Leone and Wu (2002); Hong and Kubik (2003); Emery and Li (2009)) are mostly based on their near-term forecasts rather than longer-term forecasts such as FY2. Furthermore, longer-term earnings tend to be more difficult to forecast (e.g., Chan, Karceski, and Lakonishok (2003)). Hence, effort-aversion analysts unlikely exert great effort/resources to collect private information on future earnings changes. Consequently, the forecasted earnings changes (i.e., FY2-FY1) are unlikely to contain a tremendous amount of

private information and hence might be predominantly determined by biased forecast incentives as discussed above.

If this is the case, analysts' forecasts of earnings changes can serve as a good proxy for analysts' biased forecast incentives, which should therefore be useful to predict *ex post* future forecast errors. We expect FECH to be correlated with not only the forecast errors of analysts' FY2 forecasts, but also their FY1 forecasts, as biased forecast incentives still affect analysts' FY1 forecasts, but just to a smaller extent than the longer horizon forecasts. Therefore, our second hypothesis is stated in alternative form as follows:

Hypothesis 2: Firms with higher FECH are associated with more negative FY2 and FY1 forecast errors.

Furthermore, due to the walk-down phenomenon, we would expect that such bias should be gradually guided down over the future periods. Even in the absence of management guidance that walks down the optimistic forecasts, analysts are still expected to revise down their optimistic forecasts over time to avoid the adverse impact of optimistic bias on the accuracy of short-term earnings forecasts. Hence, we also expect FECH to be correlated with the future revisions of analysts' FY1 and FY2 forecasts. Moreover, given that analysts' long-term growth forecasts are optimistically biased (e.g., La Porta (1996); Dechow and Sloan (1997)), we predict that analysts' LTG forecasts are also subject to similar biased incentives as captured in FECH and the bias in LTG forecasts may also be corrected gradually over the future periods. So our third hypothesis is summarized as follows:

Hypothesis 3: Firms with higher FECH are associated with more negative future revisions of FY1, FY2, and long-term growth forecasts.

Our final prediction concerns the return predictability of FECH. Our previous analysis predicts that FECH captures analysts' biased forecast incentives and are associated with negative forecast errors and future forecast revisions. If investors do not fully understand the predictable forecast bias driven by analysts' economic incentives, investors relying on biased forecasts would overvalue stocks with high FECH stocks and subsequently surprised by the unfavorable forecast revisions and forecast errors. Hence, the future stock returns will be negative for these firms. So if analyst biased incentives as reflected in FECH lead to mispriced equities, we would have the following prediction:

Hypothesis 4: Stocks with higher FECH tend to have lower future stock returns.

3. Data and Sample Selection

We obtain analysts' consensus forecasts from the I/B/E/S summary files. Actual EPS data are also obtained from the same source to ensure consistency with the forecasts in the treatment of nonrecurring items. The CRSP monthly returns files are our source for monthly stock returns, trading volumes, stock prices, and the number of shares outstanding. We collect fundamental data from COMPUSTAT quarterly files. Our initial sample of 1,125,889 observations includes all firm-month observations between year 1989 and 2011 with both FY1 and FY2 consensus forecasts available. The sample period starts from 1989 since this is the year when FY2 consensus forecasts and the cash flow statement data necessary to measure analysts' incentives become widely available. To avoid small firms and penny stocks, we eliminate all observations with stock price below \$5 and market capitalization below \$50 million, which reduces the sample size to 785,355. Merging with CRSP to obtain stock pricing and volume information,

Compustat to get financial data and Thomson Reuters 13f data to construct investor recognition measure further reduces the sample to 458,908 firm-month observations.

4. Empirical Results

4.1 Relative accuracy/informativeness of FY1 and FY2 forecasts as forecasts of two-year-ahead earnings

We first replicate findings of Bradshaw et al. (2012) using our sample. Forecast accuracy of contemporaneous FY1 and FY2 as forecasts for two-year-ahead earnings are computed as $ACCU12 = |FY1 - EPS2| / Price$ and $ACCU22 = |FY2 - EPS2| / Price$ respectively, where $EPS2$ are the actual earnings corresponding to analysts $FY2$ forecasts, and $Price$ is stock price at the end of the forecast month. The results are provided in Panel A of Figure 1. Consistent with Bradshaw et al. (2012), we also find that $FY2$ is less accurate than the concurrent $FY1$ as forecasts for $EPS2$ for almost all forecast horizons, even though $FY2$ is analysts' explicit forecast for $EPS2$ while $FY1$ is forecasts for a different year.

We also compare the correlations of $FY1$ and $FY2$ with $EPS2$. To mitigate the heteroskedasticity problem, we scale all variables by the stock prices at the end of the forecast month. Panel B reports the Pearson correlation coefficients. Consistent with the results in Panel A, we find that the concurrent $FY1$ forecasts are always more correlated with future actual two-year-ahead earnings $EPS2$ than analysts' explicit $FY2$ forecasts. And the difference tends to be greater for forecasts issued at longer horizons.

4.2 Determinants of analysts' forecasts of earnings change

Hypothesis 1 predicts that $FECH$ is associated with proxies of analyst biased forecast incentives even after controlling for future actual earnings changes. We test the hypothesis with the following model:

$$\begin{aligned}
FECH_{it} = & a_0 + a_1 AECH_{it} + a_2 FCF_{it} + a_3 FC_{it} + a_4 VOLUME_{it} + a_5 IREC_{it} \\
& + a_6 EVOL_{it} + a_7 RVOL_{it} + a_8 SIZE_{it} + \varepsilon_{it}
\end{aligned} \tag{1}$$

where:

$FECH_{it}$ is 100*the difference between the consensus FY2 and FY1 forecasts issued at month t (i.e. FY2-FY1), scaled by stock prices of the same time.

$AECH_{it}$ is 100*actual earnings changes scaled by stock prices.

FCF_{it} is free cash flow of the prior year divided by average total assets.

FC_{it} is financial constraints as calculated in Kaplan and Zingales (1997).

$VOLUME_{it}$ is the standardized size adjusted dollar.

$IREC_{it}$ is the standardized size adjusted investor recognition.

$EVOL_{it}$ is the standard deviation of returns on assets over the previous five years.

$RVOL_{it}$ is the standard deviation of monthly returns over the past twelve months;

$SIZE_{it}$ is the logarithm of market capitalization as of the end of the month t.

The detailed definitions of these variables are provided in the Appendix.

Table 1 reports the descriptive statistics and correlations among all variables used in model (1). Panel A shows that the mean (median) of forecast earnings changes ($FECH$) is about 1.62 (1.05) percent of stock price. In contrast, the future actual earnings changes ($AECH$) have a mean of 0.21 and median of 0.53, suggesting that analysts are on average overoptimistic about the future growth prospects of the firms that they follow. The mean and median $SIZE$ are 6.78 and 6.63 respectively, corresponding to market capitalization of about \$880 and \$757 million respectively.

Panel B of Table 1 presents the correlations matrix. Even though analysts' FY2 forecasts are less accurate than FY1, $FECH$ does contain some useful information about actual future

earnings change. The Pearson (Spearman) correlation between forecasted and actual future earnings changes is 0.257 (0.197). Consistent with our predictions, analysts' forecasts of earnings changes (FECH) are negatively correlated with FCF and SIZE, while positively correlated with FC, VOLUME, IREC, EVOL, and RVOL. Many incentive variables have higher or comparable correlations with FECH than actual future earnings changes (AECH), indicating that forecast incentives are at least as important as information in determining analysts' forecasts of earnings changes. The correlations between actual future earnings changes and the forecast incentive variables are generally low with the Pearson correlations ranging from -0.024 to 0.04 and Spearman correlations between -0.024 and 0.047.

Table 2 provides the multivariate regression results of analysts' forecasts of earnings change (FECH) on actual earnings changes as well as the incentive variables. In Panel A, we report the mean coefficients from the monthly cross-sectional regressions and the t-statistics with Newey-West adjustment for 12 lags². Columns 3 and 4 give the results for regression results with AECH as the only independent variable. Consistent with the univariate correlation results, the coefficients on AECH are positive and statistically significant, suggesting that analysts' FECH does incorporate some useful information about actual future earnings changes. However, the R-square of 7.03% indicates that the information component plays a rather minor role since it only explains a small fraction of the variation in FECH.

The next two columns examine the incremental explanatory power of the economic incentives of analysts on FECH. The results demonstrate that economic incentives are important determinants of analysts' forecasts of earnings changes. The coefficient on FCF is significantly negative and the coefficient on financial constraint is significantly positive,

² Untabulated tests show that results from pooled regressions with two-way cluster-robust standard errors by both firm and year (Peterson 2009; Gow et al 2010) are similar but stronger.

confirming that FECH tends to be larger for firms with greater investment banking business opportunities. The significant positive coefficient on VOLUME and IREC implies that FECH is higher for firms with higher trading volumes and higher investor recognitions. Optimistic longer-horizon forecasts for these firms can presumably spur more trades and thus help brokerage firms generate more trading commissions. Finally, the three variables capturing information uncertainty, EVOL, RVOL and SIZE all bear the correct signs as predicted and are statistically significant. We find that firms with higher earnings volatility, higher earnings, and smaller sizes tend to have higher FECH, consistent with analysts having greater incentive to issue optimistic longer-horizon forecasts to please managers in poorer information environment. Collectively, the incentive variables are much more important in explaining the variation in analysts' forecasts of earnings changes than the information component. Adding the incentive proxies increases the average R-square of the regression from 7.03% to 25.68%.

Panel B repeats the analysis by adding sector fixed effects. We also include a dummy variable that takes a value of 1 for stocks traded on NASDAQ to account for microstructure and volume differences between NASDAQ and NYSE/AMEX stocks as documented in Atkins and Dyl (1997). The results are similar to Panel A both qualitatively and quantitatively. The t-statistics for all the incentive variables are considerably larger in Panel B than Panel A. Furthermore, the t-statistics for all the incentive variables except VOLUME are all greater than that of AFECH.

Taken together, these results suggest that analysts' biased forecast incentives are important drivers of the cross-sectional variation in FECH. Collectively, incentives are more important than information in determining FECH. Note that we only identify three particular economic incentives in the analysis. To the extent there likely exist other unidentified biased forecast

incentives that also affect FY2 more than FY1 and therefore FECH in a similar way, the above regression may considerably understate the importance of analysts' biased forecast incentives. As hypothesis 2 predicts, if FECH mainly reflects analysts' biased forecast incentives, such biased incentives should manifest in *ex post* forecast bias in analyst forecasts. We test this hypothesis in the following section.

4.3 *FECH and analyst forecast bias*

Hypothesis 3 predicts that analyst forecasts for firms with higher FECH tend to be more optimistically biased and therefore have lower or more negative forecast errors. We calculate forecast errors as (actual EPS – EPS forecast) divided by stock prices at the end of the month when the corresponding forecasts are issued. We sort all firms into 10 deciles based on FECH each month and then compute the mean forecast errors for both FY1 and FY2 forecasts. The results are presented in Figure 2. Consistent with the prior literature that analysts tend to give optimistic forecasts, we find that the mean forecast errors are negative for all deciles. More importantly, the figure reveals a strong negative association between FECH and analyst forecast errors. For example, the mean forecast error of FY2 is about –8% of the market capitalization for the highest FECH decile. In contrast, the mean forecast error of FY2 is round –2% for the lowest FECH decile.

Interestingly, the forecast errors of FY1 also exhibit a similar pattern, showing that analyst FY1 forecasts are also more optimistic for the highest FECH decile than the rest of the portfolios. The results suggest that FECH capture some optimistic bias that affects both FY1 and FY2 forecasts. We also observe that the relation between FECH and forecast errors is not perfectly monotonic. In particular, the forecast errors for the lowest FECH deciles are more negative than the adjacent deciles. This may not be very surprising given that analysts have

little reason to be overoptimistic. Hence, low FECH may indicate analysts have some unfavorable private information about the firm and such information has not been fully incorporated into their forecasts.

4.4 *FECH and future revision of analyst forecasts*

The early results show that analysts' forecast tend to be overly optimistic for stocks with high FECH. Hypothesis 3 predicts that such optimism should be gradually corrected over time. We test this hypothesis in this section. We examine analysts FY1 and FY2 EPS forecasts, as well as their long-term growth forecasts. Analyst EPS forecasts revisions are calculated as the difference between the consensus at the end of month minus the consensus at the end of the prior month, scaled by the stock price at the end of the prior month. We calculate analysts LTG forecast revision as the difference between LTG forecasts issued at the end of the current month minus that of the prior month. The results are presented in Table 3. In Panel A, we report the mean revision in analysts' FY2 forecasts for deciles of FECH over the future six months. We find that firms in the highest FECH decile experience the greatest downward revisions in their FY2 consensus over the future six months. The mean forecast revisions for the highest FECH deciles are significantly more negative than those for both the lowest deciles. This is consistent with FY2 consensus being more optimistically biased for firms with higher FECH. The excessive bias is partially corrected in the subsequent periods as analysts' revise them down. Consistent with the results on analyst forecast errors presented earlier, the revision in FY2 forecasts are not perfectly monotonic either. Stocks in the lowest FECH decile exhibit more negative revisions than the adjacent deciles, suggesting that analysts may bear negative private information about these firms and the negative information is not fully reflected in their forecasts yet.

In Panel B of Table 3, we examine the revision in analysts' one-year ahead consensus forecasts (FY1) and find similar results. Stocks in the highest FECH decile are associated with the more negative revisions in FY1 forecasts over all the six months horizons examined. Similar to the results in Panel A, the relations between FECH and future revision are also non-monotonic, with the lowest FECH decile exhibiting slightly lower revisions than stocks in the adjacent FECH deciles. Panel C reports the mean revision in analysts' long-term growth forecasts, which again show that highest FECH firms tend to have more negative LTG forecast revision. The overall results in Table 3 confirms the results in Figure 2 that analysts are generally more optimistic biased on stocks with high FECH and such excessive optimistic bias are gradually corrected over the future periods.

4.5 *FECH and future stock returns*

In this section, we test hypothesis 4 by examining whether the market fully understands the (predictable) optimistic bias associated with FECH. If investors react to analysts' forecasts without appreciating that excessive optimistic bias in analyst forecasts associated with firms with high FECH, they will be negatively surprised by lower future realized earnings or forecast revisions. In this case, we would observe a negative association between FECH and future stock returns. We first test this prediction using portfolio tests. Specifically, we sort stocks into 10 deciles each month based FECH and the calculate the equally- and value-weighted portfolio returns for the ten portfolios as well as the hedge portfolio which takes long position in stocks in the lowest FECH decile and short position in those in the highest FECH decile.

Panel A of Table 4 reports equally weighted portfolio returns. The results show that excess returns are significantly lower for the highest FECH decile than the lowest FECH decile. The spread between the two portfolios are about 76 basis points (bps) per month. The results get

even stronger after we control for Fama-French three factors. The alpha for the hedge portfolio is about 1.1 percent per month. Further controlling for the momentum effect still leaves us with monthly alpha of 85 bps, which is statistically significant at less than 1 percent level. The highest FECH decile earns abnormal returns of -1.468 and -1.147 percent per month using three- and four-factor models respectively. Similarly to the forecast error results presented in Figure 2, the relation between FECH and future stock returns is also slightly hump shaped, with the lowest FECH portfolio also earning small negative abnormal returns. The value weighted portfolio returns are provided in Panel B of Table 4. The results are quite similar to that of Panel A except that the alphas for the lowest FECH deciles become statistically insignificant.

In Table 4, we only examine the returns in the month immediately after when FECH is calculated. We examine whether the negative future returns associated with high FECH stocks persist into longer horizons in Table 5. Panel A reports the Fama-French Four-factor Alpha for the ten equally weighted FECH deciles and the hedge portfolio over the six months after the portfolio formation. Column month 1 is the same as reported in Panel A of Table 1. Columns Month 2 to 6 reports the abnormal returns for the portfolios over the second to the sixth month after portfolio formation respectively. The results show that the highest FECH decile earns significantly negative abnormal returns over at least up to six months after portfolio formation. While the abnormal returns for the lowest FECH decile are also negative, the hedge portfolio of buying stocks with the lowest FECH and shorting stocks with the highest FECH earn significantly positive alpha over the all six months horizons. Even at the six months after portfolio formation, the hedge portfolio still earn risk adjusted returns of about 44.7 bps, which translate into annual returns of about 5.4 percent.

The value weighted portfolio returns presented in Panel B of the Table give us very similar results. The Fama-French Four-factor alphas are negative and significant for all the six months, and the hedge portfolio earn significantly positive alphas up to at least six months after portfolio formation. For the sake of brevity, we will only report equally weighted results in subsequent tests, but value weighted results are similar both qualitatively and quantitatively.

In the above tests, we control for the effect of book-to-market, size and momentum. However, one may concern that FECH simply captures the existing anomalies identified by the prior research. To alleviate the concern, we conduct cross-sectional regression tests by controlling for a few other related return predictors. Specifically, we estimate the following models:

$$FRET_{it} = a_0 + a_1 FECH_{it} + a_2 SIZE_{it} + a_3 BM_{it} + a_4 MOM_{it} + a_5 SUE_{it} + a_6 ACC_{it} + a_7 DISP_{it} + \varepsilon_{it} \quad (2)$$

where

$FRET_{it}$ is the future return for firm i after month t . We examine the monthly stock returns over the first, second, and third month, as well as the cumulative returns over the six months after portfolio formation;

$SIZE_{it}$ is the logarithm of market capitalization for firm i at month t ;

BM_{it} is the ratio of book value to market value of common equity at month t ;

MOM_{it} is the cumulative stock returns over the twelve months ending at $t-1$, as computed by Jegadeesh and Titman (1993);

SUE_{it} is the surprise of the most recent quarterly earnings, computed as the most recent realized quarterly EPS minus the corresponding consensus forecasts, scaled by the stock prices. Both the consensus forecasts and stock prices are obtained from the month immediately prior to earnings announcement. We include earnings surprises because Bernard and Thomas (1990)

show that stock prices continue to drift in the same direction as earnings surprises even after earnings announcements.

ACC_{it} is the difference between earnings and cash flows from operation scaled by average total assets. We include accruals as Sloan (1996) show that they are a robust predictor of future stock returns.

$DISP_{it}$ is the difference in within-sector decile ranks between short-term earnings growth forecasts implied from FY1 and analysts' long-term growth forecasts as calculated by Da and Warachka (2010). We also decompose $DISP$ into the two components in the regression and estimate the following model:

$$FRET_{it} = a_0 + a_1 FECH_{it} + a_2 SIZE_{it} + a_3 BM_{it} + a_4 MOM_{it} + a_5 SUE_{it} + a_6 ACC_{it} + a_7 LTG_{it} + a_7 ISTG_{it} + \varepsilon_{it} \quad (3)$$

where $ISTG$ is the implied short-term growth, calculated as $(FEPS1 - EPS0) / \max(0.05, |EPS0|)$ and LTG is analyst consensus long-term growth forecasts.

The regression results are presented in Table 6. We estimate the model cross-sectionally including sector fixed effect each month, and report the mean coefficients. For regressions where the dependent variable is one-month returns, we report the Fama-MacBeth t-statistics. For regression where the dependent variables is the cumulative six-month stock returns, we report the Fama-MacBeth t-statistics correlated for serial correlation of 5 lags using the Newey-West approach. Panel A reports the results for model (2). Consistent with the prior literature, we find that the BM , SUE , ACC and $DISP$ are positively associated with future stock returns most of the time. While the coefficients on $SIZE$ and MOM are mostly insignificant for our sample. More importantly, the coefficients on $FECH$ are negatively associated with future stock returns even after controlling for the other return predictors. The coefficients on $FECH$ are

statistically significant at less than 1 percent level for all four dependent variables. The results for model (2) where we replace the disparity measure by LTG and ISTG are provided in Panel B. We find that the coefficients on LTG are negative and marginally significant. The coefficient on ISTG is also mostly negative and insignificant most of the time. The coefficients on other control variables are similar to that of Panel A. Furthermore, FECH is still negatively associated with future returns even in presence of these set of control variables.

5. Additional Analysis and Robustness Check

5.1 *Naïve extrapolation hypothesis*

We attribute the above findings to FECH capturing analysts' biased forecast incentives. An alternative explanation is the naïve extrapolation hypothesis as described in Lakonishok et al. (1994). Specially, Lakonishok et al. show that investors' extrapolation of past performance such as sales and earnings growth contributes to the overpricing and the subsequent poor return performance of glamour stocks. One potential explanation for our findings is that analysts are also subject to the same behavior bias, and they also simply extrapolate past growth in forecasting future earnings growth. This explanation would lead to two testable predictions: First, FECH is positively correlated with past growth; second, after controlling past performance, the performance of FECH should be significantly reduced. We test the first prediction with the following model:

$$\begin{aligned}
 FECH_{it} = & a_0 + a_1 AECH_{it} + a_2 FCF_{it} + a_3 FC_{it} + a_4 VOLUME_{it} + a_5 IREC_{it} \\
 & + a_6 EVOL_{it} + a_7 RVOL_{it} + a_8 SIZE_{it} + a_9 PSG_{it} + a_{10} PEG_{it} + \varepsilon_{it}
 \end{aligned} \tag{4}$$

where *PSG* and *PEG* are sales and earnings growth over the previous three years respectively. All other variables are same as defined as early with the detailed definitions provided in the Appendix.

The regression results are provided in Panel A of Table 7. We first estimate the model as is without including the sector fixed effect. Contradicting to the naïve extrapolation hypothesis, the results in column 3 and 4 show that in presence of the other determinants, FECH is significantly negatively associated with past sales and earnings growth. The final two columns provide the regression results including sector fixed effect, and the results are similar both qualitatively and quantitatively.

We test the second prediction using portfolio approach examining whether the performance of FECH strategy are significantly weakened after controlling for the growth proxies. Specifically, we first rank all stocks in to ten deciles based on control variable *PSG* or *PEG*. Then within each decile, we further rank stocks into ten deciles based on FECH. The new strategy takes long (short) position in the 10 percent of firms with the lowest (highest) FECH portfolios in each of the decile of the control variable. We then calculate the Fama-French four-factor alpha to the strategy after controlling each of the control variables.

The results are provided in Panel B of Table 7. In the first two columns, we report the Fama-French Four-Factor alphas for the FECH strategies for the sample with complete data to calculate *PSG* and *PEG*. For this sample, the strategy still generate significant alpha over the first 5 months after forming portfolio. The alphas over the first five months horizons range from 55 to about 73 bps per month. Even though *PSG* and FECH are positively associated, controlling for *PSG* does not weaken the performance of FECH strategy by much. For example, at horizon month 1, the alpha only decreases slightly from 62 bps to 60 bps per month. The

performance of the FECH strategy decreases slightly more after controlling for PEG, but the alpha over the first month horizon is still approximately 53 bps per month and remains at the similar level over the next few months. So the overall results in Table 7 suggest that the naïve extrapolation hypothesis unlikely explain our results.

5.2 The effect of arbitrage risk on the performance of FECH strategy

We also investigate whether limited arbitrage contributes to the performance of FECH. In particular, if FECH reflects mispricing, the performance of FECH strategy should be greater for firms with greater arbitrage risk. We use idiosyncratic volatility as the proxy for arbitrage risk. We first split all stocks in to two equal sized portfolios based on idiosyncratic volatility each month. Then within each portfolio, we further rank stocks into ten deciles based on FECH and compare the Fama-French four-factor alphas to the strategy takes long (short) position in firms with the lowest (highest) FECH portfolios in each of the three portfolios. The results using equally weighted portfolio returns are presented in Panel A of Table 8³. We find that FECH generate positive alpha of about 22 bps for stocks with low idiosyncratic volatility (i.e., firms with low arbitrage risk), which is insignificant at conventional levels. In contrast, the strategy generates four-factor alphas of about 66 bps for stocks in the high idiosyncratic volatility group. The hedge returns are greater than that of the lowest arbitrage risk group and are statistically significant at less than 1 percent level.

5.3 The effect of investor sentiment on the performance of FECH strategy

We also examine whether investor sentiment contributes to the performance of FECH for two reasons. First, analyst biased incentives to obtain investment banking business and generate trading commissions should be higher when investor sentiment is higher as it is easy for firm to raise capital and investors also trade more aggressively during these period. Second, if FECH

³ Results using value weighting scheme are similar.

reflects mispricing, the performance of FECH strategy should be greater when investor sentiment is higher. We download the investor sentiment data from Professor Jeffery Wurgler's website as developed in Baker and Wurgler (2006). Half of the sample years with sentiment index lower than the median are classified as low sentiment period and the rest are classified as high sentiment period. We then report the Fama-French four factor returns to the ten FECH deciles and the hedge portfolios. The results are provided in Panel B of Table 8. FECH strategy generates four-factor alpha of about 48 bps over the low investor sentiment period. In contrast, during high investor sentiment period, the strategy generates significant monthly alpha of approximately 1.13%.

5.4 *Additional analysis*

We also conduct a battery of other additional analysis to test the robustness of our results.

First, we split our sample period to two sub-periods with the "Early Period" covering year 1989 to 1999 and the "Recent Period" including year 2000 to 2011 and examine whether the strategy generates consistent performance over the two sub-periods. The results presented in Panel A of Table 9 show that the FECH based strategy that longs stocks with the lowest FECH and shorts stocks with the highest FECH generate Four-Factor alpha of about 77 and 86 bps per month in the early and recent sub-periods respectively. Both alphas are statistically significant at less than 1 percent level.

Second, a recent paper by Chen, Novy-Marx and Zhang (2011) propose an alternative three-factor model based on Q-theory, which including a market factor ($MKT-Rf$), an investment factor (r_{INV}), and a profitability factor (r_{ROE}). As a robustness check, we also use this alternative three-factor model to test the performance of the FECH strategy⁴. The results are

⁴ The detailed description on how to construct the investment and the return-on-asset factors can be found on page 4-6 of Chen et al. (2012).

presented on Panel B of Table 9. The strategy generates significant monthly alpha of around 0.83 and 1.05% per month after controlling for the alternative three factors, suggesting that Q-theory does not explain away our results.

Third, Novy-Marx (2012) also proposes an alternative four-factor model based on the gross profit anomaly document in the same paper. Novy-Marx suggests that the model reduces the magnitude of abnormal returns a wide range of anomalies-based trading strategies. We therefore also test our strategy by controlling this alternative four-factor model. The results presented in Panel C of Table 9 suggest that the monthly alpha to the FECH strategy still remains statistically significant and reaches approximately 69 and 92 bps for the equally- and value-weighted portfolios respectively.

Finally, if analyst biased incentives drives the return predictability of FECH, we would also expect that the effect to be stronger for firms with higher identifiable biased forecast incentives, as high FECH for these firms are more likely driven by analysts incentives instead of measurement errors. Consistent with this prediction, untabulated results show that FECH strategy generates significantly higher abnormal returns among firms with lower free cash flows, higher financial constraints, high trading volume, and smaller size.

6. Conclusions

Analysts' two-year-ahead EPS forecasts are of critical importance to equity valuations. However, prior research documents that as a forecast for two-year ahead actual earnings, analysts FY2 forecasts are even less accurate than their own FY1 forecasts. We hypothesize and find that the difference between analysts FY1 and FY2 forecasts, or FECH is largely driven by their biased forecast incentives and information about future actual earnings changes only

explain a small fraction of the variation. Consistent with FECH reflects analysts intentional forecast bias, we find that it is a robust predictor of future forecast errors and forecast revisions. Specifically, we show that both analysts' FY1 and FY2 forecasts tend to be more overly optimistic compared with ex post realized earnings and they are also more likely to be revised downward for firms with extremely high FECH. Our analysis also demonstrates that stocks with extremely high FECH consistently earn low risk-adjusted future returns, which indicates that the stock market does not fully appreciate the biased forecast incentives reflected in FECH.

This paper offers several avenues for future research. First, we show that analysts' FY1 consensus are more accurate than FY2 consensus as forecasts for two-year-ahead earnings. Future research may investigate whether better proxies can be obtained by combining information in FY1 and FY2, as well as other information in the time-series of earnings. Second, future research can also better model the incentive components of FECH by teasing out the information components, which could give rise to a better measure of analysts' ex ante forecast incentive and therefore a stronger predictor of future forecast errors and stock returns. Third, this paper focuses on the firm-level analysis. Future research may also investigate how analyst specific forecast incentives affect forecast earnings changes and the related implications.

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Appendix: Variable Definitions

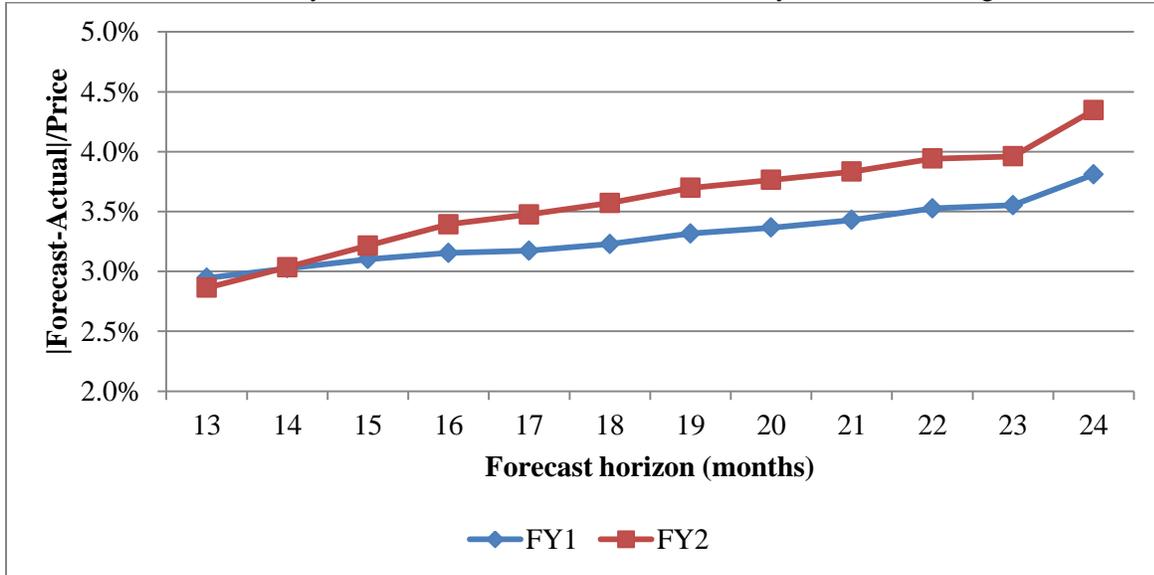
- FECH:* Forecasted earnings changes from the current fiscal year to the following, calculated as $100*(FEPS2-FEPS1)/PRICE$, where *FEPS2* is analyst consensus EPS forecasts for fiscal year 2; *FEPS1* is the consensus EPS forecasts for fiscal year 1; *PRICE* is the stock prices as of the month end when the two consensus forecasts are issued.
- AFECH:* Actual earnings changes from the current year to the following year, calculated as $100*(EPS2-EPS1)/PRICE$, where *EPS2* is the actual EPS forecasts for fiscal year 2; *EPS1* is the actual EPS forecasts for fiscal year 1; *PRICE* is the stock prices as of the month end when the corresponding consensus forecasts *FEPS1* and *FEPS2* are issued.
- FCF:* Free cash flow of the prior year (OANCF + IVNCF), scaled by average total assets.
- FC:* Financial constraints measure as calculated in Kaplan and Zingales (1997), i.e. $FC = -1.001909*(\text{net income} + \text{depreciation and amortization expense})/\text{lagged total assets} + 0.2826389*(\text{Total assets} - \text{book value of common equity} - \text{deferred tax balance sheet} + \text{market cap of common equity})/\text{total assets} + 3.139193* \text{Total debt}/\text{total assets} - 39.3678*\text{total dividend}/\text{lagged total assets} - 1.314759* \text{cash and equivalent}/\text{lagged total assets}$.
- VOLUME:* Trading volume, calculated as the standardized decile rank of size adjusted dollar volume over the past twelve months. Specifically, we first rank all stocks each month into 10 size (market capitalization) deciles. Within each size decile, we further sort firms into 10 deciles based on trading volume. The 10 portfolios with the highest (lowest) trading volume are assigned a value of 9 (0). We then standardize the rank into a range of 0 to 1, by dividing it by 9.
- IREC:* Investor recognition, calculated similar to Richardson et al. (2012). We first compute institutional ownership breadth (IOB) as the number of institutional investors holding a stock divided by the total number of institutional investors filing 13f filings in the same quarter. We then rank all stocks each month into 10 size (market capitalization) deciles. Within each size decile, we further sort firms into 10 deciles based on IOB. The 10 portfolios with the highest (lowest) IOB are assigned a value of 9 (0). We then standardize the rank into a range of 0 to 1, by dividing it by 9 to obtain the measure of *IREC*.
- EVOL:* Earnings volatility, calculated as the standard deviation of return on assets over the previous five years.
- RVOL:* Returns volatility, calculated as the standard deviation of monthly stock returns over the past 12 months.
- SIZE:* Logarithm of market capital (in million) as of the current month end.
- ISTG:* Implied short-term growth, calculated as $(FEPS1-EPS0)/\max(0.05, |EPS0|)$.
- LTG:* Analyst consensus long-term growth forecasts.

- BM:* Book-to-market ratio, calculated as the book value of the immediate prior quarter (ending at least three months before the current month), divided by the market value of equity at the end of current month.
- MOM:* Momentum factor, calculated as the cumulative stock returns over the past nine months with one month lag.
- SUE:* Standardized unexpected earnings, calculated as the $100 * (EPSQ - FEPSQ) / PRC$, where *EPSQ* is the actual EPS for the prior quarter; *FEPSQ* is the corresponding quarterly EPS forecasts issued at the month before the earnings announcement of the prior quarter; *PRC* is the stock price at the month end before the earnings announcement of the prior quarter.
- ACC:* Accruals of the prior fiscal year, calculated as (cash flow from operating activities – net income)/average total assets.
- DISP:* Disparity measure as calculated in Da and Warachka (2011), i.e. within sector decile rank of *ISTG* – within sector decile rank of *LTG*.
- PSG:* Past average sales growth, calculated as the mean of sales growth (*SGR*) over the prior three years, where *SGR* is calculated as $(SALES - lagged\ SALES) / lagged\ SALES$. *SALES* is the annual sales revenue.
- PEG:* Past earnings growth, calculated as mean EPS growth over the past three years. Annual *EPS* growth calculated as $(EPS - lagged\ EPS) / \max(0.05, |lagged\ EPS|)$.
- IDVOL:* Idiosyncratic volatility, calculated as the square root of mean squared errors of the market model regression using monthly stock returns over the past three years.

Figure 1: Comparison of FY1 and FY2 as forecasts for two years ahead earnings

This figure compares the usefulness of FY2 consensus and FY1 as forecasts for two-year-ahead earnings. Panel A compares the accuracy of the two forecasts and Panel B compares their correlations with two-year-ahead actual earnings. We calculate forecast accuracy as the difference between forecasts and actual, scaled by stock prices at the end of the FY2 forecast month. Forecast horizon is the number of months from the date of FY2 forecasts to the announcement of the actual two-year-ahead earnings. To mitigate the heteroskedasticity problem, we scale both actual earnings and earnings forecasts by stock prices as of the month of forecast date in compute the correlations in Panel B.

Panel A: Forecast accuracy for FY2 and FY1 as forecasts for two year ahead earnings



Panel B: Correlations of FY1 and FY2 with two-year-ahead actual earnings

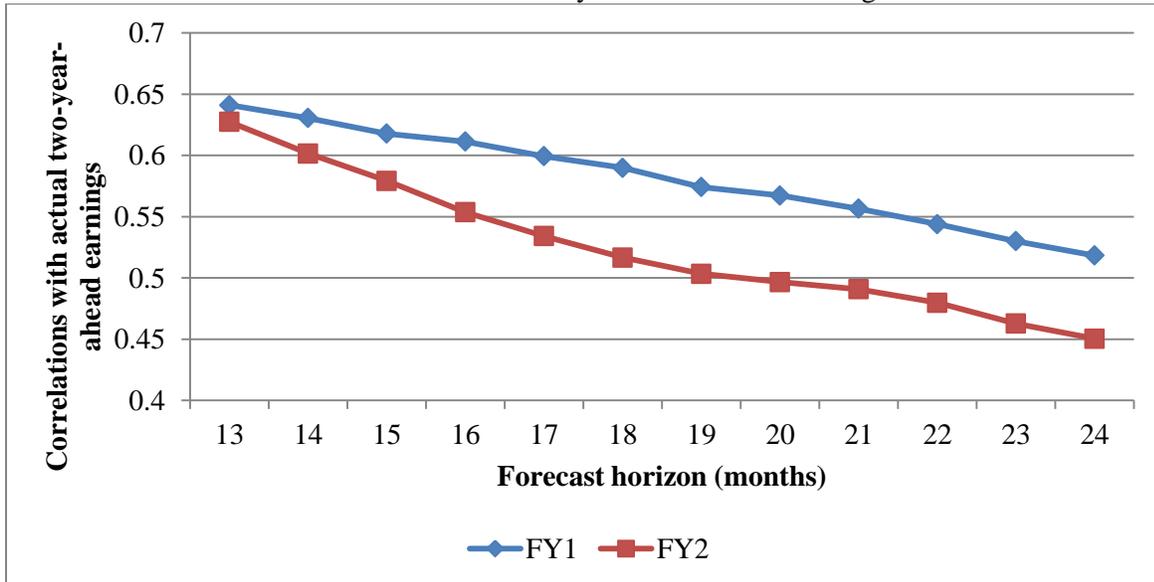


Figure 2: Forecast errors for stocks with different levels of FECH

This figure plots the mean forecast errors of analysts FEPS1 and FEPS2 forecasts for deciles of FECH. We rank all firms with available data into ten deciles each month based on FECH. We then calculate the mean forecast errors for analyst consensus FEPS1 and FEPS2 forecasts for the ten portfolios. Forecast errors are calculated as $(actual\ EPS - EPS\ forecast)$ divided by stock prices at the end of the month when the corresponding forecasts are issued.

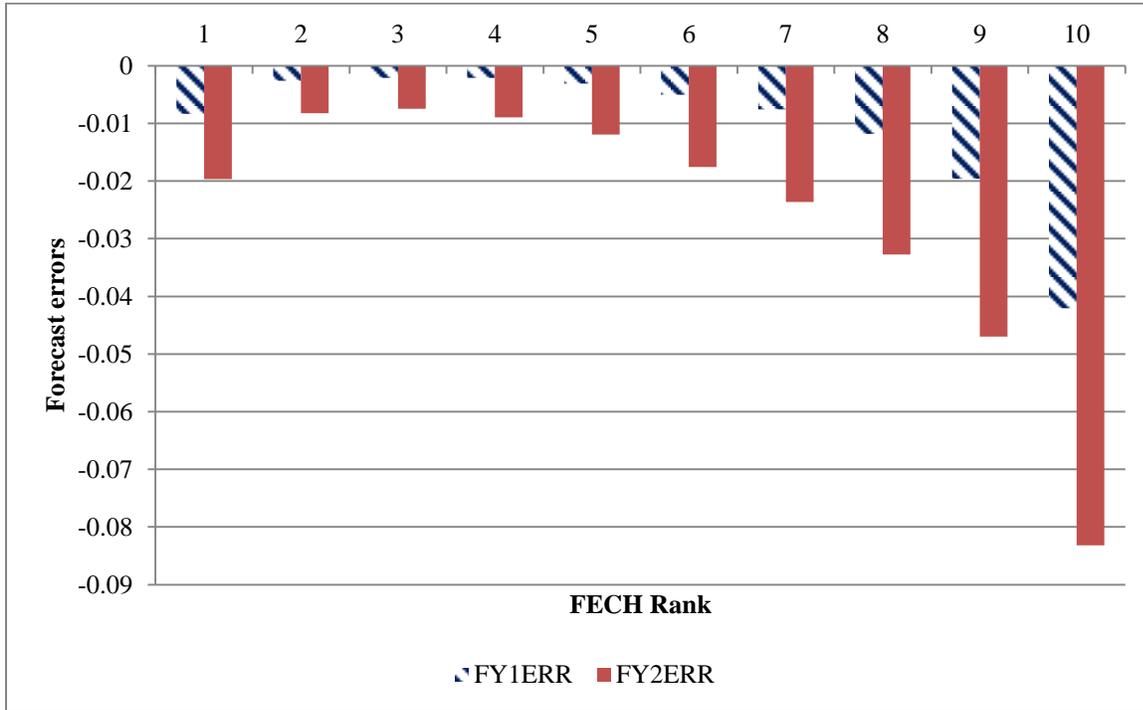


Table 1: Descriptive statistics and correlation matrix

This table provides the descriptive statistics for variables used in regression model (1).

$$FECH_{it} = a_0 + a_1 AECH_{it} + a_2 FCF_{it} + a_3 FC_{it} + a_4 VOLUME_{it} + a_5 IREC_{it} + a_6 EVOL_{it} + a_7 RVOL_{it} + a_8 SIZE_{it} + \varepsilon_{it}$$

All variables are as defined in the appendix.

Panel A: Descriptive statistics for variables used in model (1)

	N	Mean	STD	P1	Q1	Median	Q3	P99
FECH	458,908	1.621	2.051	-1.764	0.652	1.053	1.887	9.829
AECH	458,908	0.210	4.691	-14.600	-1.083	0.529	1.724	12.590
FCF	458,908	-0.013	0.141	-0.500	-0.059	0.011	0.067	0.237
FC	458,908	0.419	1.033	-3.040	-0.061	0.452	1.032	2.441
VOLUME	458,908	0.501	0.312	0.000	0.222	0.556	0.778	1.000
IREC	458,908	0.501	0.314	0.000	0.222	0.556	0.778	1.000
EVOL	458,908	0.048	0.065	0.001	0.012	0.025	0.055	0.332
RVOL	458,908	0.118	0.068	0.033	0.070	0.102	0.148	0.362
SIZE	458,908	6.780	1.532	4.117	5.601	6.637	7.826	10.286

Panel B: Correlation matrix for variables used in model (1), with Pearson (Spearman) correlation on the upper (lower) diagonals.

	FECH	AECH	FCF	FC	VOLUME	IREC	EVOL	RVOL	SIZE
FECH		0.257	-0.153	0.143	0.162	0.061	0.220	0.295	-0.270
AECH	0.197		0.018	0.025	-0.024	-0.024	0.040	0.039	0.032
FCF	-0.162	0.020		-0.196	-0.093	0.071	-0.192	-0.220	0.182
FC	0.187	0.047	-0.243		0.121	-0.020	0.049	0.167	-0.047
VOLUME	0.204	-0.014	-0.065	0.133		0.510	0.225	0.346	0.040
IREC	0.077	-0.024	0.071	-0.032	0.507		-0.002	0.015	0.044
EVOL	0.280	0.041	-0.008	0.031	0.309	0.045		0.414	-0.204
RVOL	0.348	0.029	-0.156	0.210	0.390	0.044	0.480		-0.281
SIZE	-0.340	0.018	0.177	-0.052	0.031	0.033	-0.218	-0.329	

Table 2: Regression results of forecast earnings change on analysts' forecast incentives

This table present the regression results of model (1):

$$FECH_{it} = a_0 + a_1 AECH_{it} + a_2 FCF_{it} + a_3 FC_{it} + a_4 VOLUME_{it} + a_5 IREC_{it} + a_6 EVOL_{it} + a_7 RVOL_{it} + a_8 SIZE_{it} + \varepsilon_{it}$$

We estimate the model cross-sectionally each month and report the mean coefficients and the t-statistics with Newey-West adjustment for autocorrelation of 12 lags. All variables are as defined in the appendix. *, **, and *** indicate significance at 10%, 5% and 1% levels respectively.

Panel A: Cross-sectional regressions without sector fixed effect

	Predicted Sign	Model I		Model II	
		Estimate	t-stat	Estimate	t-stat
<i>Intercept</i>		1.510	24.00	1.899	10.83
<i>AECH</i>	+	0.105	6.48	0.110	7.37
<i>FCF</i>	-			-0.894	-3.84
<i>FC</i>	+			0.166	8.09
<i>VOLUME</i>	+			0.306	3.95
<i>IREC</i>	+			0.335	5.60
<i>EVOL</i>	+			4.989	4.72
<i>RVOL</i>	+			5.292	11.28
<i>SIZE</i>	-			-0.229	-11.60
<i>Avg R-square</i>		7.03		25.68	
<i>Avg. N</i>		1,738		1,738	

Panel B: Cross-sectional regressions with sector fixed effect

	Predicted Sign	Model I		Model II	
		Estimate	t-stat	Estimate	t-stat
<i>Intercept</i>		2.0446	13.72	2.410	11.36
<i>AECH</i>	+	0.1032	6.38	0.107	7.95
<i>FCF</i>	-			-0.964	-12.81
<i>FC</i>	+			0.171	11.83
<i>VOLUME</i>	+			0.344	5.24
<i>IREC</i>	+			0.300	8.84
<i>EVOL</i>	+			5.215	8.34
<i>RVOL</i>	+			5.355	10.98
<i>SIZE</i>	-			-0.229	-12.01
<i>Avg R-square</i>		14.40		30.40	
<i>Avg. N</i>		1,738		1,738	

Table 3: Analyst revision over the future six months for stocks with different levels of FECH

This table examines the revisions of analysts' consensus forecasts for the ten FECH deciles over the first six months after portfolio formation. We form portfolios each month by ranking firms into ten deciles based on FECH. Column "Month 1" to "Month 6" provide the mean revisions for these portfolios over the first- through sixth month after portfolio formation. Panel A, B and C report the results for revisions of analyst one- and two-year ahead EPS forecasts and long-term growth forecasts respectively. The t-stat is the t-statistics of the monthly revision time-series. *, **, *** indicate statistical significance at 1, 5 and 10 percent levels respectively.

Panel A: FY2 Revision		Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Lowest	Mean Revision	-0.094***	-0.111***	-0.124***	-0.126***	-0.128***	-0.133***
	T-stat	-4.58	-5.98	-6.93	-8.28	-8.61	-8.78
2	Mean Revision	-0.028***	-0.04***	-0.046***	-0.053***	-0.054***	-0.064***
	T-stat	-2.76	-4.05	-4.90	-6.38	-7.10	-8.04
3	Mean Revision	-0.016**	-0.031***	-0.038***	-0.045***	-0.05***	-0.053***
	T-stat	-2.55	-4.31	-5.84	-7.32	-8.24	-8.38
4	Mean Revision	-0.022***	-0.033***	-0.045***	-0.051***	-0.058***	-0.064***
	T-stat	-4.03	-5.34	-7.13	-8.46	-8.33	-9.51
5	Mean Revision	-0.031***	-0.047***	-0.057***	-0.068***	-0.075***	-0.082***
	T-stat	-6.60	-7.45	-7.92	-9.33	-9.13	-9.95
6	Mean Revision	-0.061***	-0.074***	-0.087***	-0.102***	-0.112***	-0.119***
	T-stat	-9.97	-10.39	-10.36	-10.44	-10.46	-9.89
7	Mean Revision	-0.100***	-0.117***	-0.129***	-0.138***	-0.149***	-0.156***
	T-stat	-13.22	-12.31	-12.21	-12.02	-12.19	-12.09
8	Mean Revision	-0.164***	-0.178***	-0.192***	-0.206***	-0.215***	-0.22***
	T-stat	-16.28	-14.57	-13.53	-12.77	-11.83	-11.79
9	Mean Revision	-0.271***	-0.278***	-0.283***	-0.284***	-0.29***	-0.294***
	T-stat	-19.29	-16.39	-15.3	-14.26	-13.17	-12.52
Highest	Mean Revision	-0.498***	-0.485***	-0.473***	-0.453***	-0.454***	-0.445***
	T-stat	-19.05	-16.99	-15.27	-14.11	-13.35	-12.77
Lowest-Highest	Mean Revision	0.404***	0.374***	0.348***	0.327***	0.326***	0.312***
	T-stat	21.44	19.03	16.17	13.98	13.98	13.52

Panel B: FY1 Revision

FECH Deciles		Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Lowest	Mean Revision	-0.082***	-0.09***	-0.098***	-0.111***	-0.109***	-0.11***
	T-stat	-10.8	-10.5	-10.42	-11.37	-11.56	-12.27
2	Mean Revision	-0.026***	-0.028***	-0.035***	-0.045***	-0.045***	-0.053***
	T-stat	-6.75	-8.02	-9.46	-8.64	-10.05	-11.40
3	Mean Revision	-0.017***	-0.025***	-0.031***	-0.038***	-0.043***	-0.047***
	T-stat	-6.73	-8.96	-9.68	-10.74	-11.5	-12.55
4	Mean Revision	-0.019***	-0.029***	-0.036***	-0.044***	-0.048***	-0.053***
	T-stat	-7.91	-9.46	-12.05	-12.41	-13.77	-14.47
5	Mean Revision	-0.028***	-0.039***	-0.048***	-0.057***	-0.062***	-0.068***
	T-stat	-10.25	-11.27	-11.99	-14.86	-14.3	-14.22
6	Mean Revision	-0.052***	-0.062***	-0.072***	-0.085***	-0.092***	-0.099***
	T-stat	-13.79	-14.99	-15.00	-15.79	-16.16	-15.66
7	Mean Revision	-0.081***	-0.099***	-0.109***	-0.113***	-0.122***	-0.131***
	T-stat	-17.3	-18.07	-17.22	-17.65	-18.38	-17.11
8	Mean Revision	-0.132***	-0.148***	-0.159***	-0.168***	-0.176***	-0.178***
	T-stat	-20.3	-18.79	-18.36	-17.85	-16.56	-16.39
9	Mean Revision	-0.213***	-0.23***	-0.234***	-0.239***	-0.244***	-0.249***
	T-stat	-21.74	-19.93	-18.90	-18.8	-16.93	-16.74
Highest	Mean Revision	-0.439***	-0.428***	-0.426***	-0.408***	-0.402***	-0.397***
	T-stat	-18.57	-18.35	-17.3	-16.42	-15.95	-15.99
Lowest-Highest	Mean Revision	0.357***	0.338***	0.328***	0.297***	0.293***	0.287***
	T-stat	18.33	18.34	16.40	15.00	15.02	15.26

Panel C: LTG Revision

FECH Deciles		Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Lowest	Mean Revision	-0.065***	-0.058***	-0.054***	-0.054***	-0.05***	-0.046***
	T-stat	-8.97	-7.97	-7.27	-7.23	-6.55	-6.08
2	Mean Revision	-0.034***	-0.034***	-0.037***	-0.034***	-0.035***	-0.043***
	T-stat	-6.64	-6.88	-6.90	-6.48	-6.48	-7.71
3	Mean Revision	-0.029***	-0.035***	-0.035***	-0.036***	-0.04***	-0.04***
	T-stat	-6.32	-8.23	-8.49	-7.64	-8.31	-8.14
4	Mean Revision	-0.033***	-0.033***	-0.039***	-0.049***	-0.051***	-0.05***
	T-stat	-7.08	-7.61	-7.87	-9.93	-10.19	-9.9
5	Mean Revision	-0.047***	-0.053***	-0.054***	-0.054***	-0.053***	-0.06***
	T-stat	-10.11	-10.76	-10.12	-10.29	-8.96	-10.81
6	Mean Revision	-0.058***	-0.062***	-0.069***	-0.076***	-0.079***	-0.077***
	T-stat	-10.49	-10.22	-10.98	-11.62	-11.82	-11.7
7	Mean Revision	-0.07***	-0.078***	-0.076***	-0.079***	-0.085***	-0.083***
	T-stat	-10.27	-9.85	-10.08	-10.98	-12.35	-11.37
8	Mean Revision	-0.086***	-0.091***	-0.092***	-0.093***	-0.086***	-0.09***
	T-stat	-10.58	-11.57	-11.9	-11.18	-11.11	-11.77
9	Mean Revision	-0.09***	-0.087***	-0.092***	-0.087***	-0.09***	-0.084***
	T-stat	-10.58	-10.05	-11.41	-11.25	-11.09	-10.16
Highest	Mean Revision	-0.089***	-0.087***	-0.083***	-0.083***	-0.083***	-0.084***
	T-stat	-11.03	-11.28	-11.02	-10.79	-11.44	-11.84
Lowest-Highest	Mean Revision	0.023***	0.029***	0.029***	0.028***	0.033***	0.038***
	T-stat	3.14	3.70	4.03	3.74	4.40	5.44

Table 4: Returns to FECH trading strategy

This table tests whether a strategy that takes long position in stocks with low FECH and short position in stocks with high FECH generate significant abnormal returns after controlling for known risk factors. We form portfolios each month by ranking firms into ten deciles based on FECH. We then examine the stock returns over the immediate next month. We calculate the monthly time-series returns to each of the ten portfolios, as well as the hedge portfolios. We report mean excess returns, Fama-French three- and four-factor alphas to these portfolios. Excess returns are calculated as the portfolio returns minus risk free rate. Fama-French three-factor alpha is the intercept of the regression of monthly portfolio returns on MKTRF, HML, and SMB, while the four-factor alpha is the intercept of the regression that includes UMD as an additional factor. Panel A and B report the results for equally weighted and value weighted portfolio returns respectively. *, **, *** indicate statistical significance at 1, 5 and 10 percent levels respectively.

Panel A: Equally weighted average returns to FECH deciles

FECH Rank	Excess Return		Fama French Three-factor Alpha		Fama French Four-factor Alpha	
	Return	T-stat	Alpha	T-stat	Alpha	T-stat
Lowest	0.271	0.73	-0.369***	-2.74	-0.298**	-2.21
2	0.520*	1.84	0.017	0.17	-0.059	-0.63
3	0.647**	2.47	0.133*	1.83	0.079	1.10
4	0.718***	2.58	0.152*	1.94	0.115	1.45
5	0.735**	2.48	0.115	1.36	0.125	1.46
6	0.733**	2.24	0.060	0.63	0.118	1.24
7	0.617*	1.71	-0.128	-1.36	-0.031	-0.35
8	0.380	0.99	-0.398***	-3.50	-0.256**	-2.42
9	0.171	0.40	-0.693***	-5.73	-0.481***	-4.78
Highest	-0.491	-0.96	-1.468***	-8.28	-1.147***	-7.92
Lowest-Highest	0.762***	3.18	1.100***	5.61	0.850***	4.68

Panel B: Value weighted average returns to FECH deciles

FECH Rank	Excess Return		Fama French Three-factor Alpha		Fama French Four-factor Alpha	
	Return	T-stat	Alpha	T-stat	Alpha	T-stat
Lowest	0.505	1.50	-0.032	-0.20	-0.086	-0.53
2	0.455*	1.75	0.027	0.27	-0.039	-0.40
3	0.654***	2.68	0.212***	2.84	0.174**	2.33
4	0.567**	2.15	0.070	0.78	0.041	0.45
5	0.618**	2.15	0.042	0.43	0.081	0.82
6	0.592*	1.87	-0.034	-0.32	0.050	0.47
7	0.485	1.39	-0.214*	-1.94	-0.111	-1.04
8	0.500	1.30	-0.260*	-1.94	-0.134	-1.03
9	0.344	0.82	-0.494***	-3.29	-0.299**	-2.16
Highest	-0.216	-0.43	-1.211***	-6.10	-0.924***	-5.19
Lowest-Highest	0.721**	2.29	1.179***	4.45	0.839***	3.43

Table 5: Fama French Four-factor Alpha over the future six months to FECH deciles

This table examines the hedge returns to a strategy that takes long position in stocks with low FECH and short position in stocks with high FECH over the first six months after portfolio formation. We form portfolios each month by ranking firms into ten deciles based on FECH. Column “Month 1” to “Month 6” provide the Fama-French Four-factor alphas to these portfolios over the first- through sixth month after portfolio formation. Panel A and B report the results for equally weighted and value weighted portfolio returns respectively. *, **, *** indicate statistical significance at 1, 5 and 10 percent levels respectively.

Panel A: Equally weighted portfolios							
FECH Deciles		Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Lowest	Alpha	-0.298**	-0.202	-0.133	-0.205	-0.298**	-0.327**
	T-stat	-2.21	-1.41	-0.92	-1.35	-2.06	-2.35
2	Alpha	-0.059	-0.037	0.036	0.071	0.124	0.095
	T-stat	-0.63	-0.40	0.33	0.64	1.20	0.96
3	Alpha	0.079	0.040	0.137*	0.185**	0.169**	0.127
	T-stat	1.10	0.54	1.67	2.24	2.08	1.55
4	Alpha	0.115	0.121	0.081	0.120	0.089	0.152*
	T-stat	1.45	1.54	0.97	1.36	1.01	1.73
5	Alpha	0.125	0.126	0.111	0.072	0.094	0.131
	T-stat	1.46	1.30	1.15	0.74	1.00	1.45
6	Alpha	0.118	-0.002	-0.105	-0.078	-0.060	0.018
	T-stat	1.24	-0.01	-1.07	-0.82	-0.64	0.19
7	Alpha	-0.031	-0.056	-0.137	-0.097	-0.143	-0.195**
	T-stat	-0.35	-0.58	-1.39	-0.99	-1.59	-2.13
8	Alpha	-0.256**	-0.340***	-0.314***	-0.344***	-0.302***	-0.189*
	T-stat	-2.42	-3.50	-2.82	-3.06	-2.79	-1.87
9	Alpha	-0.481***	-0.506***	-0.549***	-0.541***	-0.440***	-0.482***
	T-stat	-4.78	-4.74	-5.09	-4.61	-3.62	-3.90
Highest	Alpha	-1.147***	-1.111***	-1.079***	-0.920***	-0.926***	-0.774***
	T-stat	-7.92	-7.36	-6.70	-5.15	-4.91	-4.08
Lowest-Highest	Alpha	0.850***	0.909***	0.946***	0.716***	0.628***	0.447**
	T-stat	4.68	4.75	4.45	3.27	2.81	2.22

Panel B: Value weighted portfolios

FECH Deciles		Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Lowest	Alpha	-0.086	-0.067	0.057	0.033	-0.062	-0.099
	T-stat	-0.53	-0.39	0.34	0.20	-0.39	-0.62
2	Alpha	-0.039	0.057	0.033	0.095	0.158*	0.086
	T-stat	-0.40	0.63	0.34	0.99	1.74	0.96
3	Alpha	0.174**	0.179**	0.295***	0.262***	0.122	0.165**
	T-stat	2.33	2.02	3.22	2.91	1.33	1.96
4	Alpha	0.041	0.104	-0.045	-0.125	0.004	0.139
	T-stat	0.45	1.06	-0.50	-1.32	0.04	1.40
5	Alpha	0.081	-0.030	-0.019	0.126	0.049	-0.019
	T-stat	0.82	-0.27	-0.16	1.16	0.46	-0.17
6	Alpha	0.049	-0.055	-0.042	-0.117	-0.184*	-0.081
	T-stat	0.47	-0.48	-0.37	-1.05	-1.64	-0.73
7	Alpha	-0.111	-0.114	-0.186	-0.006	-0.003	-0.127
	T-stat	-1.04	-0.90	-1.51	-0.05	-0.03	-1.02
8	Alpha	-0.134	-0.238*	-0.208	-0.278**	-0.268*	-0.088
	T-stat	-1.03	-1.80	-1.48	-2.03	-1.90	-0.61
9	Alpha	-0.299**	-0.399**	-0.416**	-0.476***	-0.416***	-0.470***
	T-stat	-2.16	-2.55	-2.55	-3.20	-2.64	-2.77
Highest	Alpha	-0.924***	-0.910***	-0.775***	-0.721***	-0.641***	-0.645***
	T-stat	-5.19	-4.46	-3.72	-3.32	-3.06	-3.03
Lowest-Highest	Alpha	0.839***	0.843***	0.831***	0.754***	0.579**	0.545**
	T-stat	3.43	3.18	3.05	2.63	2.16	2.04

Table 6: Regressions of future stock returns on FECH and other return predictors

This table reports the results for regressions of future stock returns on *FECH* as well as other control variables. Panel A and B presents the results of the following two models:

$$FRET_s = \beta_0 + \beta_1 FECH + \beta_2 SIZE + \beta_3 BM + \beta_4 MOM + \beta_5 SUE + \beta_6 ACC + \beta_7 PEGR + \beta_8 DISP + \varepsilon$$

$$FRET_s = \beta_0 + \beta_1 FECH + \beta_2 SIZE + \beta_3 BM + \beta_4 MOM + \beta_5 SUE + \beta_6 ACC + \beta_7 PEGR + \beta_8 LTG + \beta_9 ISTG + \varepsilon$$

where *FRET*s are future stock returns. We examine future stock returns over the first (Column “Month 1”), second (Column “Month 2”), third (Column “Month 3”) month, as well as the cumulative stock returns over the six months (Column “Month 1 to 6”) following the month when *FECH* is calculated.

Definitions of other variables can be found in the appendix. *, **, *** indicate statistical significance at 1, 5 and 10 percent levels respectively.

Panel A: Regression controlling for *DISP* and other control variables

	Month 1		Month 2		Month 3		Month 1 to 6	
	Coeff	t_stat	Coeff	t_stat	Coeff	t_stat	Coeff	t_stat
<i>INTERCEPT</i>	0.999	2.09	0.756	1.58	0.729	1.55	3.850	1.52
<i>FECH</i>	-0.089	-2.87	-0.108	-3.33	-0.128	-3.91	-0.479	-2.97
<i>SIZE</i>	-0.019	-0.41	0.006	0.12	0.019	0.42	0.099	0.50
<i>BM</i>	0.211	3.15	0.118	1.76	0.092	1.33	0.688	1.76
<i>MOM</i>	0.207	1.25	0.198	1.28	0.131	0.88	0.690	0.60
<i>SUE</i>	0.482	8.64	0.201	3.49	0.062	1.10	1.570	5.33
<i>ACC</i>	2.268	4.71	2.106	4.22	1.789	3.72	12.403	4.90
<i>DISP</i>	0.043	2.44	0.033	1.86	0.025	1.42	0.179	1.63
<i>Avg R-square</i>	9.97		9.76		9.50		11.75	
<i>Avg. N</i>	2,050		2,050		2,050		2,050	

Panel B: Regression controlling for *LTG* and *ISTG* and other control variables

	Month 1		Month 2		Month 3		Month 1 to 6	
	Coeff	t_stat	Coeff	t_stat	Coeff	t_stat	Coeff	t_stat
<i>INTERCEPT</i>	1.261	2.81	1.092	2.41	1.135	2.56	5.924	2.13
<i>FECH</i>	-0.080	-2.71	-0.098	-3.16	-0.117	-3.76	-0.425	-2.78
<i>SIZE</i>	-0.031	-0.72	-0.016	-0.36	-0.011	-0.25	-0.037	-0.18
<i>BM</i>	0.176	3.07	0.059	1.04	0.019	0.32	0.319	1.03
<i>MOM</i>	0.239	1.47	0.232	1.52	0.176	1.22	0.875	0.77
<i>SUE</i>	0.520	10.15	0.247	4.50	0.105	1.88	1.787	6.87
<i>ACC</i>	2.425	5.29	2.236	4.72	1.847	4.07	12.689	5.20
<i>LTG</i>	-0.018	-1.79	-0.019	-1.90	-0.020	-2.01	-0.113	-2.01
<i>ISTG</i>	0.012	0.27	-0.041	-0.93	-0.086	-1.96	-0.222	-0.96
<i>Avg R-square</i>	10.57		10.34		10.05		12.49	
<i>Avg. N</i>	2,050		2,050		2,050		2,050	

Table 7: Does extrapolation hypothesis explain the results?

This table examine whether the FECH strategy can be explained by the extrapolation hypothesis. In Panel A, we augment regression model in Table 2 and regressing FECH on past earnings and sales growth and other determinants. We estimate the model cross-sectionally each month and report the mean coefficients and the t-statistics with Newey-West adjustment for autocorrelation of 12 lags. All variables are as defined in the appendix. In Panel B, we examine whether FECH strategy still generates significant hedge returns after controlling for past growth (PSG/PEG). Specifically, we first rank all stocks in to ten deciles based on PSG/PEG. Then within each decile, we further rank stocks into ten deciles based on FECH. The new strategy takes long (short) position in the 10 percent of firms with the lowest (highest) FECH portfolios in each of the decile of the control variable. *, **, *** indicate statistical significance at 1, 5 and 10 percent levels respectively. Variable definitions can be found in the Appendix.

Panel A: Regression of FECH on past growth and other determinants

	Predicted Sign	Estimate	t-stat	Estimate	t-stat
<i>Intercept</i>		1.991	12.19	2.513	12.63
<i>AECH</i>	+	0.106	7.30	0.102	7.92
<i>FCF</i>	-	-1.058	-5.04	-1.002	-13.38
<i>FC</i>	+	0.160	7.56	0.173	11.97
<i>VOLUME</i>	+	0.484	6.61	0.493	7.80
<i>IREC</i>	+	0.227	3.77	0.206	5.66
<i>EVOL</i>	+	5.175	4.97	5.241	9.00
<i>RVOL</i>	+	5.582	11.54	5.433	10.96
<i>SIZE</i>	-	-0.228	-12.12	-0.228	-12.53
<i>PSG</i>	+	-0.533	-6.22	-0.395	-4.51
<i>PEG</i>	+	-0.302	-8.50	-0.314	-9.64
<i>Sector fixed effect</i>		NO		YES	
<i>Avg R-square</i>		28.10		31.69	
<i>Avg. N</i>		1,641		1,641	

Panel B: Performance of FECH strategy after controlling for past growth

		Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
<i>FECH</i>	<i>Alpha</i>	0.620	0.694	0.731	0.579	0.548	0.316
	<i>T-stat</i>	3.29	3.55	3.47	2.61	2.38	1.45
<i>Controlled for PSG</i>	<i>Alpha</i>	0.603	0.602	0.697	0.533	0.525	0.291
	<i>T-stat</i>	5.86	5.70	6.41	4.78	4.65	2.64
<i>Controlled for PEG</i>	<i>Alpha</i>	0.534	0.592	0.646	0.518	0.404	0.324
	<i>T-stat</i>	5.23	5.78	5.95	4.65	3.61	2.99

Table 8: The effect of arbitrage risk and investor sentiment on the performance of FECH strategy

This table examines how the performance of the FECH strategy varies with arbitrage risk and investment sentiment. Panel A reports the results for subsample split on arbitrage risk. We use idiosyncratic volatility as a proxy for arbitrage risk. Each month, we split the sample into two subsamples based on the median of idiosyncratic volatility and then compute the Fama-French four factor returns to the ten FECH deciles. In Panel B, we split the whole sample period into low and high sentiment periods based on the sentiment index as developed by Baker and Wurgler (2006). Half of the sample years with sentiment index lower than the median are classified as low sentiment period and the rest are classified as high sentiment period. We then report the Fama-French four factor returns to the ten FECH deciles and the hedge portfolios.

Panel A: FECH strategy for firms with low and high idiosyncratic volatility.

FECH Rank	Low IDVOL group		High IDVOL group	
	Alpha	T-stat	Alpha	T-stat
Lowest	0.189	1.88	-0.212	-1.26
2	0.127	1.29	-0.091	-0.75
3	0.197	1.93	0.066	0.66
4	0.183	1.84	-0.126	-1.29
5	0.256	2.36	0.073	0.67
6	0.297	2.86	0.060	0.54
7	0.287	2.78	-0.255	-1.95
8	0.316	3.01	-0.239	-1.86
9	0.222	2.08	-0.441	-3.51
Highest	-0.027	-0.24	-0.867	-4.73
Lowest-Highest	0.216	1.46	0.655	2.83

Panel B: FECH strategy for high & low sentiment period

FECH Rank	Low Sentiment period		High Sentiment period	
	Alpha	T-stat	Alpha	T-stat
Lowest	-0.344	-2.06	-0.203	-1.01
2	-0.071	-0.58	-0.085	-0.62
3	-0.033	-0.29	0.069	0.66
4	-0.090	-0.88	0.164	1.36
5	-0.061	-0.58	0.149	1.14
6	-0.084	-0.78	0.168	1.12
7	-0.121	-1.16	0.003	0.02
8	-0.280	-2.41	-0.294	-1.65
9	-0.525	-3.92	-0.392	-2.4
Highest	-0.825	-4.02	-1.331	-5.89
Lowest-Highest	0.481	1.85	1.127	4.28

Table 9: Subsample period performance and alternative risk models

This table examines whether the FECH strategy is robust to subsample periods and to controlling for alternative risk proxies. Panel A reports the Fama-French four-factor alpha to the FECH strategy for subsample period of 1989 to 1999 and 2000-2011. Portfolios are formed following the procedure described in Table 4. Panel B tests whether the strategy that takes long position in stocks with low FECH and short position in stocks with high FECH generates significant alpha under the alternative three-factor models of Chen, Novy-Marx and Zhang (2011). We report the alphas to FECH based portfolios using the alternative three- and four-factor alphas. The alternative three factor model alpha is the intercept of the hedge returns on the market risk premium, a profitability factor and an investment factors as calculated by Chen et al. (2011):

$$HGRET = \alpha + \beta_{MKT}(MKT-Rf) + \beta_{INV}r_{INV} + \beta_{ROE}r_{ROE} + \varepsilon$$

We also augment the model with an additional momentum factor, i.e. the alternative four-factor model:

$$HGRET = \alpha + \beta_{MKT}(MKT-Rf) + \beta_{INV}r_{INV} + \beta_{ROE}r_{ROE} + \beta_{UMD}r_{UMD} + \varepsilon$$

*, **, *** indicate statistical significance at 1%, 5% and 10% levels respectively.

Panel A: FECH strategy for early and recent periods

FECH Rank	Early Period (1989-1999)		Recent Period (2000-2011)	
	Alpha	T-stat	Alpha	T-stat
Lowest	0.043	0.25	-0.652***	-3.36
2	-0.120	-1.07	-0.086	-0.62
3	0.008	0.08	0.088	0.89
4	0.019	0.17	0.186*	1.79
5	0.004	0.03	0.260**	2.34
6	-0.093	-0.74	0.330***	2.62
7	-0.102	-0.89	0.093	0.71
8	-0.218*	-1.65	-0.161	-1.04
9	-0.225*	-1.68	-0.565***	-3.82
Highest	-0.724***	-3.80	-1.514***	-7.02
Lowest-Highest	0.767***	3.08	0.862***	3.29

Panel B: Chen, Novy-Marx and Zhang (2011) alternative three-factor model

FECH Rank	Equally weighted portfolio		Value weighted portfolio	
	Alpha	T-stat	Alpha	T-stat
Lowest	0.182	1.11	0.369**	2.35
2	0.194	1.54	0.067	0.64
3	0.131	1.23	0.085	1.15
4	0.117	1.03	-0.097	-1.18
5	0.086	0.70	-0.135	-1.37
6	0.089	0.62	-0.118	-1.06
7	0.056	0.34	-0.118	-0.94
8	-0.139	-0.75	-0.089	-0.58
9	-0.191	-0.95	-0.163	-0.95
Highest	-0.652***	-2.91	-0.678***	-3.10
Lowest-Highest	0.833***	3.87	1.047***	3.56

Panel C: Novy-Marx alternative four-factor alpha

FECH Rank	Equally weighted portfolio		Value weighted portfolio	
	Alpha	T-stat	Alpha	T-stat
Lowest	0.428**	2.28	0.483***	2.91
2	0.229*	1.73	0.081	0.75
3	0.090	0.80	0.022	0.28
4	0.056	0.46	-0.173*	-1.77
5	0.082	0.62	-0.137	-1.24
6	0.136	0.89	-0.063	-0.54
7	0.108	0.62	-0.115	-0.9
8	0.026	0.13	0.067	0.43
9	0.035	0.16	-0.049	-0.28
Highest	-0.264	-0.99	-0.442*	-1.95
Lowest-Highest	0.691***	3.22	0.924***	3.39

Table X to be deleted: The effect of identifiable incentives on the performance of FECH strategy

In this table, we examine the hedge returns to FECH strategy for subsample split on proxies for identifiable incentives. Specifically, we first rank all stocks into three equal sized portfolios based on incentive proxies each month. Then within each portfolio, we further rank stocks into ten deciles based on FECH. The table reports the Fama-French four-factor alphas to the strategy takes long (short) position in firms with the lowest (highest) FECH portfolios in each of the three portfolios. We also compare the hedge returns between firms with the highest value and those with the lowest idiosyncratic volatility. *, **, *** indicate statistical significance at 1, 5 and 10 percent levels respectively. Variable definitions can be found in the Appendix.

Panel A: Subsample split on FCF

		<i>Month 1</i>	<i>Month 2</i>	<i>Month 3</i>	<i>Month 4</i>	<i>Month 5</i>	<i>Month 6</i>
<i>Low</i>	<i>Alpha</i>	1.213	1.130	1.242	1.137	0.934	0.508
	<i>T-stat</i>	4.44	4.03	4.35	4.01	3.20	1.93
<i>Medium</i>	<i>Alpha</i>	0.185	0.356	0.474	0.226	0.212	-0.025
	<i>T-stat</i>	0.91	1.65	1.94	0.96	0.86	-0.11
<i>High</i>	<i>Alpha</i>	0.244	0.307	0.459	0.383	0.431	0.288
	<i>T-stat</i>	1.14	1.37	2.03	1.69	1.91	1.31
<i>High-Low</i>	<i>Alpha</i>	-0.968	-0.823	-0.783	-0.754	-0.504	-0.220
	<i>T-stat</i>	-3.43	-2.85	-2.79	-2.85	-1.79	-0.81

Panel B: Subsample split on FC

		<i>Month 1</i>	<i>Month 2</i>	<i>Month 3</i>	<i>Month 4</i>	<i>Month 5</i>	<i>Month 6</i>
<i>Low</i>	<i>Alpha</i>	0.492	0.445	0.373	0.434	0.314	0.008
	<i>T-stat</i>	2.31	2.04	1.64	1.86	1.29	0.03
<i>Medium</i>	<i>Alpha</i>	0.676	0.853	0.831	0.703	0.665	0.462
	<i>T-stat</i>	3.09	4.06	3.71	2.98	3.00	1.98
<i>High</i>	<i>Alpha</i>	0.948	1.083	1.006	0.834	0.839	0.482
	<i>T-stat</i>	4.00	4.17	3.69	2.87	2.78	1.78
<i>High-Low</i>	<i>Alpha</i>	0.456	0.637	0.633	0.400	0.525	0.474
	<i>T-stat</i>	1.88	2.52	2.36	1.46	1.82	1.77

Panel C: Subsample split on VOLUME

		<i>Month 1</i>	<i>Month 2</i>	<i>Month 3</i>	<i>Month 4</i>	<i>Month 5</i>	<i>Month 6</i>
<i>Low</i>	<i>Alpha</i>	0.232	0.354	0.453	0.239	0.340	0.216
	<i>T-stat</i>	1.42	2.08	2.52	1.30	1.90	1.24
<i>Medium</i>	<i>Alpha</i>	0.499	0.683	0.577	0.533	0.443	0.353
	<i>T-stat</i>	2.67	3.57	2.97	2.52	2.11	1.68
<i>High</i>	<i>Alpha</i>	0.937	0.844	1.169	0.735	0.745	0.252
	<i>T-stat</i>	3.21	2.72	3.75	2.27	2.34	0.83
<i>High-Low</i>	<i>Alpha</i>	0.704	0.490	0.716	0.496	0.405	0.036
	<i>T-stat</i>	2.38	1.60	2.30	1.52	1.32	0.12

Panel D: Subsample split on IREC

		<i>Month 1</i>	<i>Month 2</i>	<i>Month 3</i>	<i>Month 4</i>	<i>Month 5</i>	<i>Month 6</i>
<i>Low</i>	<i>Alpha</i>	0.800	0.818	0.883	0.792	0.721	0.293
	<i>T-stat</i>	3.92	3.90	4.12	3.70	3.23	1.39
<i>Medium</i>	<i>Alpha</i>	1.273	1.232	1.094	0.843	0.946	0.703
	<i>T-stat</i>	6.15	5.71	5.16	3.86	4.05	3.09
<i>High</i>	<i>Alpha</i>	0.774	0.745	0.940	0.653	0.575	0.432
	<i>T-stat</i>	3.08	2.91	3.43	2.19	1.89	1.51
<i>High-Low</i>	<i>Alpha</i>	-0.025	-0.073	0.057	-0.139	-0.146	0.139
	<i>T-stat</i>	-0.10	-0.29	0.21	-0.50	-0.50	0.52

Panel E: Subsample split on EVOL

		<i>Month 1</i>	<i>Month 2</i>	<i>Month 3</i>	<i>Month 4</i>	<i>Month 5</i>	<i>Month 6</i>
<i>Low</i>	<i>Alpha</i>	0.360	0.458	0.608	0.590	0.450	0.473
	<i>T-stat</i>	1.74	1.97	2.47	2.40	1.86	1.94
<i>Medium</i>	<i>Alpha</i>	0.157	0.342	0.447	0.303	0.228	0.067
	<i>T-stat</i>	0.84	1.79	2.34	1.48	1.07	0.32
<i>High</i>	<i>Alpha</i>	0.713	0.844	0.928	0.787	0.730	0.288
	<i>T-stat</i>	2.48	2.86	3.08	2.57	2.30	1.05
<i>High-Low</i>	<i>Alpha</i>	0.354	0.386	0.320	0.197	0.280	-0.185
	<i>T-stat</i>	1.13	1.16	0.93	0.59	0.84	-0.58

Panel F: Subsample split on RVOL

		<i>Month 1</i>	<i>Month 2</i>	<i>Month 3</i>	<i>Month 4</i>	<i>Month 5</i>	<i>Month 6</i>
<i>Low</i>	<i>Alpha</i>	0.228	0.389	0.459	0.337	0.249	0.253
	<i>T-stat</i>	1.67	2.77	3.09	2.43	1.79	1.77
<i>Medium</i>	<i>Alpha</i>	0.467	0.696	0.740	0.682	0.424	0.356
	<i>T-stat</i>	2.81	4.11	4.17	3.56	2.21	1.74
<i>High</i>	<i>Alpha</i>	0.531	0.580	0.842	0.571	0.517	0.305
	<i>T-stat</i>	1.99	2.09	2.85	1.84	1.61	1.11
<i>High-Low</i>	<i>Alpha</i>	0.302	0.191	0.383	0.235	0.267	0.052
	<i>T-stat</i>	1.14	0.67	1.27	0.77	0.88	0.19

Panel G: Subsample split on SIZE

		<i>Month 1</i>	<i>Month 2</i>	<i>Month 3</i>	<i>Month 4</i>	<i>Month 5</i>	<i>Month 6</i>
<i>Low</i>	<i>Alpha</i>	1.201	1.071	1.261	0.799	0.730	0.353
	<i>T-stat</i>	5.02	4.32	5.13	3.00	2.50	1.38
<i>Medium</i>	<i>Alpha</i>	0.422	0.490	0.530	0.522	0.275	0.338
	<i>T-stat</i>	1.83	2.12	2.09	1.99	1.10	1.44
<i>High</i>	<i>Alpha</i>	0.302	0.391	0.491	0.503	0.384	0.115
	<i>T-stat</i>	1.37	1.63	1.88	1.84	1.40	0.45
<i>High-Low</i>	<i>Alpha</i>	-0.898	-0.680	-0.770	-0.295	-0.346	-0.237
	<i>T-stat</i>	-3.08	-2.28	-2.60	-0.95	-1.04	-0.72