Mind the Gap: The Non-Fundamental Role of Earnings Days*

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Abstract

We construct a new measure—the Return-Earnings Gap (*REG*)—that captures the market's relative (mis)reaction to earnings surprises. About 50% of the earnings-day return associated with *REG* reverses subsequently, with the reversal being strikingly slow, taking about three years. *REG* feeds back into and distorts market participants' belief formation, predicting subsequent analyst forecast errors, corporate actions associated with mispricing, and the divergence of anomaly returns. A simple structural model of market participants' expectation formation corroborates these findings. Our results show that earnings-day returns contain a substantial non-fundamental component with long-term effects, contrasting with the predominant fundamental view of earnings days.

JEL Classification: G00, G12, G14, G40, G41

Keywords: investor beliefs, earnings announcements, misreaction, analyst expectations, mispricing, anomalies

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1 Introduction

Extending the traditional view of financial markets as fundamental information aggregators (Hayek, 1945; Grossman, 1976; Holthausen and Verrecchia, 1988), recent research pays great attention to biases, which can be responsible for stock price deviations from fundamentals and take an important part in the longstanding debate on risk vs. mispricing (e.g., Kozak et al., 2018).[1] On the other side, earnings announcements are considered crucial events for the incorporation of fundamental information into prices. This fundamental view is supported by the significant relation of earnings-day returns to earnings surprises and the fact that earnings days contribute to mispricing correction on average (e.g., Engelberg et al., 2018).

In this paper, we complement the predominant fundamental view by uncovering the non-fundamental role of earnings days. We propose a new measure, the *R*eturn-*E*arnings *G*ap (*REG*), and provide new evidence unveiling that the *relative gap* between the market reaction to earnings and earnings surprises is non-fundamental in nature with broad market implications affecting prices, actions, and belief formation.

Precisely, we show that (I) the announcement return associated with this gap strongly reverts. The reversal is economically large and very slow, taking up to three years, which is in stark contrast to the widely studied return continuation (drift) associated with the earnings surprise or the market reaction itself.[2] (II) *REG* feeds back into and distorts

[1]The formation of biased expectations can stem from various mechanisms and include extrapolative and diagnostic beliefs (Greenwood and Shleifer, 2014; Cassella and Gulen, 2018; Bordalo et al., 2019; Da et al., 2021; Ertan et al., 2022), confirmation bias (Nickerson, 1998; Pouget et al., 2017; Hirshleifer et al., 2021; Cookson et al., 2023; Kapons and Kelly, 2024), sticky belief dynamics (Bordalo et al., 2019), and catch-all sentiment (De Long et al., 1990; Baker and Wurgler, 2006).

[2]Starting from the work of Bernard and Thomas (1989, 1990), the empirical research on the relation of earnings returns to earnings surprises is extensive. Numerous papers focus on price continuations beyond the earnings day, known as the post-earnings-announcement drift (e.g., Chordia and Shivakumar, 2006; Doyle et al., 2006; Livnat and Mendenhall, 2006). Such a drift is also found for additional non-earnings information released on earnings days, such as revenue surprises or text-based measures of soft information (Jegadeesh and Livnat, 2006; Loughran and McDonald, 2016).

market participants' belief formation. It predicts institutional trading and subsequent analyst forecast errors in the same direction and predicts corporate actions associated with mispricing. (III) Circling back to prices, we show that *REG* is associated with a long-lasting divergence from the correction paths of anomaly portfolios, providing a more nuanced perspective on the role of earnings days for the correction of mispricing.

Altogether, our paper reveals that earnings days can be a platform for the emergence of biases in expectation formation, mispricing buildups that are slow to correct, and deviations from anomaly correction paths. A given earnings announcement can either reduce and alleviate or induce and amplify biases and mispricing, depending on whether the classical fundamental effect or the non-fundamental component, as established in this paper, dominates. Consequently, *REG* can be valuable in determining whether earnings days are in a correction or an amplification regime.

The *R*eturn-*E*arnings *G*ap (*REG*), central to our paper, is constructed based on the difference between the independent rankings of the earnings-day return and the unexpected earnings, where both rankings are assigned based on their past realized distributions. By this design, *REG* is able to capture the gap between the market participants' reaction and the released cash flow information on earnings announcement days in a non-parametric way. A higher (lower) gap indicates a more positive (negative) response by market participants for a given earnings surprise.

We do not make any ex-ante assumptions on whether or not *REG* is driven by other (non-earnings) information released on earnings days. Indeed, *REG* could reflect a rational market reaction to other fundamentals (Hand et al., 2022) or to "soft" information (Loughran and McDonald, 2016) released together with the earnings announcement. In such cases, *REG* should be unrelated to subsequent returns, future analyst forecast errors, and mispricing dynamics. Alternatively, *REG* may reflect market participants' recognition of firm mispricing and lead to lower analyst forecast errors and an accelerated mispricing correction (e.g., Engelberg et al., 2018). The third possibility is that a higher (lower) *REG* is not driven by fundamentals, but reflects investors' excessive optimism (pessimism) toward the firm's prospects. In this case, it may lead to higher future analyst forecast errors, an increase in firm mispricing that is reversed subsequently, and deviations from anomaly corrections. Empirically, we find unequivocal support in favor of the third alternative.

Our empirical analysis starts with the relation between *REG* and subsequent stock returns. In stark contrast to the established post-earnings-announcement drift, the return component associated with *REG* features a pronounced reversal behavior, as highlighted by Figure 1. Around 50% of the earnings-day effect is reversed subsequently, and the reversal is strikingly slow, taking about three years. At the same time, the component of earnings-day returns associated with earnings surprises or the abnormal earnings-day returns themselves lead to price continuations that do not revert in the long run. While these well-known continuation dynamics are consistent with a (partly delayed) reaction to fundamentals, the long-term reversal associated with *REG* highlights the non-fundamental role of earnings days.

The observed long-term reversal dynamics motivate the important question whether and to what extent the non-fundamental component of earnings-day returns affects and distorts the expectation formation of other market participants. We first show that *REG* predicts institutional net buying pressure in the days after the earnings announcement, suggesting that *REG* captures investors' beliefs that are reflected via their trading activities. Moreover, *REG* positively predicts next-quarter analyst forecast errors (*AFE*), controlling for current *AFE*, firm mispricing scores (Jacobs, 2016), and a battery of stock-specific variables. This result indicates that analysts fail to disentangle noise and biases from the fundamental information contained in the market reaction to earnings, such that the non-fundamental component feeds back to analysts in a way that distorts their expectation formation. Remarkably, the predictability of analyst forecast errors by *REG* extends up to 12 quarters ahead, in line with the slow reversal of *REG*-related returns.

Next, we examine the predictive relation between *REG* and corporate variables, where we focus on Stambaugh et al.'s (2012; 2015) firm characteristics that are closely related to firm mispricing. We find that *REG* predicts a significant increase in aggregate mispricing scores over several quarters. When distinguishing between management and performance-related variables (Stambaugh and Yuan, 2017), our results show that *REG* positively predicts management actions such as stock issuance and investment, while it is also an indicator of future disappointment in performance, as captured by a lower return on assets and gross profitability. These findings indicate a strong relation of *REG* with management optimism (see also Gennaioli et al., 2016), which is, however, not justified by an increase in future performance. Altogether, the disparity between earnings surprises and the market response on earnings days is a significant predictor of institutional trading, future analyst forecast errors, and mispricing-related corporate variables, indicating that it is strongly connected to the emergence of biases in market participants' expectations.

We conduct a number of additional tests and robustness checks of these main results. In particular, we demonstrate that our main findings do not critically hinge on technical details of the *REG* measure construction. We additionally show that the observed effects of *REG* on analyst expectations and corporate variables are economically and statistically significant on both the positive and the negative side, which helps rule out alternative explanations that yield a one-sided effect.[3] Moreover, our results remain intact when explicitly controlling for non-earnings information, including information from earnings call transcripts (e.g., Loughran and McDonald, 2016) as well as additional fundamental releases (Hand et al., 2022), and also hold for the pre-2002 period, where no additional fundamentals were released on earnings days.

We proceed by connecting the realization of REG to the performance of anomaly portfolios. Given REG's long-term impact on expectations and the slow return reversal, we expect its effect on anomaly returns to be long-lasting, taking time to correct. Indeed, we find that when REG is "against" the direction that is expected according to the path of mispricing correction, there is a stark deviation from the correction path that is accompanied by a slow subsequent convergence. Strikingly, the initial deviation is almost fully reversed in the longer run, leading to an overall return at a three-year horizon that is similar to cases where REG is "with" the direction of the correction. Again, no such reversal is observable when conditioning on earnings-day returns or earnings surprises. Our collective findings reveal new dynamics of mispricing and anomaly returns originating from the non-fundamental component of earnings-day returns. REG allows us to cleanly capture the emergence of mispricing and to track its correction.

The distinctive dynamics of expectations and returns in response to REG motivate additional tests on the expectation formation and its dependence on the information environment. First, we show that the predictability of analyst forecast errors through REG is more pronounced for analysts who react more quickly and are thus more strongly affected by the potentially biased signal. Second, we provide strong evidence that analysts

[3]For example, strategic analyst behavior driven by career concerns may explain upward-biased analyst forecasts in response to a positive REG (Hong and Kubik, 2003), but would not yield downward-biased forecasts for negative REG.

exhibit a higher sensitivity to *REG* when they do not have high-quality private signals and are thus more reliant on public signals. For that, we utilize both the heterogeneity in analysts' industry concentration and past forecast accuracy as proxies for information quality as well as the Global Analyst Research Settlement as a quasi-exogenous event causing a negative shock to the analysts' information set. Third, exploring the firm information environment, we find the relation between *REG* and firm mispricing scores to be more pronounced for firms that do not provide earnings guidance and for firms with higher earnings volatility. Our combined findings suggest that a weaker information environment leads to a stronger response of expectations to *REG*, and a more pronounced spillover of potential biases.

A final feature of the *REG* measure is that it allows us to distinguish cases where the market's reaction is in the same or the opposite direction of analysts' contemporaneous forecast errors. Predictions from the behavioral literature suggest that similar reactions by different groups of investors can lead to confirmation bias and amplification effects (Pouget et al., 2017; Hirshleifer et al., 2021; Cookson et al., 2023; Kapons and Kelly, 2024). We explore this possibility in two settings. First, we find that analysts' subsequent forecast errors induced by *REG* are more pronounced when the market reaction confirms analysts' prior expectations, consistent with a confirmation bias. Second, we find support for an amplification of *REG*'s predictive relation to mispricing-related corporate variables when *REG* is in the same direction as contemporaneous analyst forecast errors. Altogether, when *REG* confirms pre-existing biases, then it induces a stronger bias in future expectations, as reflected both by analyst forecast errors and by mispricing-related corporate variables.

In the paper appendix, we present a simple structural model of dynamic expectation formation with biases that corroborates the empirical findings of our paper. In the model, there are two agents—stock market investors and analysts/managers—who dynamically update their expectations of earnings growth rates and try to infer each other's private signals. When analysts/managers observe the market response to earnings and this market response is not predominantly reflective of fundamental information, they falsely interpret an abnormal market reaction as an informative signal, which distorts their expectation formation. As a consequence, *REG* predicts analyst forecast errors and corporate decisions. Moreover, the model takes into account that analysts' and managers' updated expectations feed back again into investors' beliefs. As a result, it takes a long time until the initial returns associated with *REG* are reversed and the mispricing is corrected. The model demonstrates that the dynamic expectation formation between different types of agents, as revealed through the non-fundamental role of earnings days in this paper, is critical for understanding pricing patterns and the persistence of biases in financial markets.

Related literature Our paper contributes to the literature on market participants' belief formation and their processing of fundamental news. Earnings announcements are by far the most widely-studied news events in the cross-section of firms, with a focus on stock returns on and after the earnings day and their relation to earnings surprises. Interestingly, not much is known about the component of earnings-day returns that is not attributable to the earnings surprise. Attempting to explain this "gap" by fundamentals, Loughran and McDonald (2016) construct text-based measures to capture soft information, and Hand et al. (2022) consider additional fundamentals released on earnings days. Both types of information incrementally contribute to the predictable variation in earnings-day returns and induce a drift after the earnings day (e.g., Jegadeesh and Livnat, 2006). In contrast, our paper uncovers the non-fundamental component of the market reaction on earnings days. The long-term reversal associated with *REG* contrasts with the fundamental component of earnings-day returns and highlights that the market's misreaction can have broad, long-term effects.

We also provide a new perspective on the question how analysts react to earnings information and incorporate it into their forecasts, which started out from the papers by De Bondt and Thaler (1990), Mendenhall (1991), and Abarbanell and Bernard (1992). Our paper is the first to investigate how the market (mis)reaction to earnings influences and biases analysts' future expectations. As such, we add to recent research that examines how analysts weight different private and publicly available signals. For instance, Gerken and Painter (2023) show that analysts rely more strongly on geographically local signals when less firm-wide information is available. In the context of macroeconomic forecasts, Bianchi et al. (2022) show that professional forecasters put too much weight on their private component and too little weight on objective information, resulting in a bias.[4] A contemporaneous and complementary paper by Chaudhry (2024) argues that stock price increases which are unrelated to cash flow news raise analysts' cash flow expectations. Our paper, on the other hand, focuses on the release of cash flow information and investigates how analyst expectations and management actions are influenced by the market (mis)reaction to such cash flow news.

Moreover, our paper contributes to the literature on risk, mispricing, and anomaly returns. Extending the view that the arrival of public information generally accelerates the correction of mispricing, we show that the one-day return associated with *REG* leads to a slow mispricing correction and substantially modulates longer-term anomaly returns. Our findings thus complement Engelberg et al. (2018) and provide a way to distinguish between convergence and divergence from the correction path based on the direction of

[4] In general, biased expectations of market participants have also been documented about credit spreads (Bordalo et al. 2018), interest rates (Cieslak 2018), cash flow growth (De la O and Myers 2021), and macroeconomic quantities such as GDP growth and inflation (e.g., Bordalo et al., 2020; Bianchi et al., 2022).

REG. Importantly, conditioning on earnings-day returns or earnings surprises does not affect anomaly returns in a similar way. In addition, our results add to recent evidence on the potential contribution of institutional investors to firm mispricing (Edelen et al., 2016; DeVault et al., 2019), as we find that the disproportionate market response to earnings is significantly related to abnormal institutional trading in the same direction.

Finally, our paper highlights the interplay between different market participants and the propagation of biases between them, with the goal of stimulating the emerging but still relatively small literature on this topic. Large parts of the literature interpret analyst expectations as a proxy for investor expectations in general. Important exceptions are Ke et al. (2023), who find that the relaxation of short-sale constraints (and increased price efficiency) positively influences analyst forecast accuracy. Malmendier and Shanthikumar (2007) examine to what extent traders take into account the analysts' affiliation bias when interpreting their recommendations, and Hirshleifer et al. (2019) show that investors understand analysts' potential decision fatigue. In our paper, the distinction between investor beliefs and analyst or management expectations is critically important, as we find that a biased market response to earnings news (reflecting investor beliefs) propagates to analysts and managers and, in turn, results in a slow correction of firm mispricing.

2 Measures Construction and Data

*2.1 The Return-Earnings Gap (*REG*) Measure*

We propose a new measure that is designed to capture the relative gap between earnings surprises and the corresponding stock market reaction. While the conceptual idea behind our measure can be translated to other fundamental news events, we focus on earnings announcements as they provide an ideal setting of scheduled, regular events that provide important cash flow information. Moreover, an extensive literature considers earnings surprises (SUE) as a quantitative measure of the released earnings news and relates them to firms' earnings-day stock returns.

Building on these foundations, our REG measure captures the extent to which the stock price reaction to the earnings surprise deviates from the average response, employing a non-parametric ranking approach. In particular, we calculate, for each firm and earnings announcement day, the independent rankings of the market response and of the fundamental earnings surprise relative to their rolling past distributions. REG captures the disparity between both rankings, such that large values indicate that the market reaction deviates strongly from what one would expect on average.

We describe the construction of REG in detail. To improve the comparability of earnings surprises and earnings-day returns across firms, we employ adjusted standardized earnings surprises ($AdjSUE$) and characteristic-adjusted abnormal returns ($DGTW$, according to Daniel et al. 1997). We first discuss the computation of $AdjSUE$. For each earnings announcement, we obtain the actual earnings per share (EPS), the median of analysts' EPS forecasts, and the standard deviation of their EPS forecasts. Following Mendenhall (2004), we compute the standardized unexpected earnings (SUE) as follows:

$$SUE_{i,t} = \frac{EPS_{i,t}^{Actual} - \text{Med}(EPS_{i.t}^{Estimate})}{\text{SD}(EPS_{i.t}^{Estimate})} \tag{1}$$

$EPS_{i,t}^{Actual}$ is the firm's actual EPS reported on the earnings announcement day, where after-market-close announcements are shifted to the next trading day. $\text{Med}(EPS_{i.t}^{Estimate})$ and $\text{SD}(EPS_{i.t}^{Estimate})$ are the last available median and standard deviation of analysts' EPS forecasts reported in I/B/E/S prior to the earnings announcement day. We use I/B/E/S unadjusted information and adjust the actual EPS, the median, and the standard deviation of analyst forecasts for dividends and splits using the cumulative adjustment factors from the Center for Research in Security Prices (CRSP) database.

Small or value firms may have different properties than large or growth firms. In addition, announcements on different weekdays or in different months may result in systematically different magnitudes of earnings surprises. To make *SUE* comparable across stocks, we keep the residual, which we denote as *AdjSUE*, from the following regression:

$$SUE_{i,t} \;=\; \beta_0 + \beta_1 LnSIZE_{i,t} + \beta_2 LnBM_{i,t} + \sum_{d=Mon}^{Sat} D_d + \sum_{m=Jan}^{Nov} D_m + \epsilon_{i,t}, \tag{2}$$

where $LnSIZE_{i,t}$ and $LnBM_{i,t}$ are the natural log of the size and book-to-market ratio of stock i as of day t, respectively. D_d and D_m are day-of-week and month-of-year dummies. The regression residual $\epsilon_{i,t}$ is our $AdjSUE_{i,t}$ component for stock i on earnings day t. Finally, to prevent a look-ahead bias, we estimate equation (2) based on a one-year backward rolling window up to day t for each earnings day t.

Next, to construct the second component of our *REG* measure, the stock price reaction, we compute daily characteristic-adjusted abnormal returns following the approach of Daniel et al. (1997), which accounts for differences in expected returns that are associated with firm size, book-to-market ratio, and momentum. We denote the daily abnormal return of stock i on day t as $DGTW_{i,t}$.

With both components at hand, we turn to construct our *REG* measure. For an earnings announcement of firm i on day t, we independently sort all earnings announcements in our sample within a one-year backward rolling window (including day t), on the one hand by their

$DGTW$ and on the other hand by their *AdjSUE*, into bins. In our main specification, we use 1,000 bins.[5] We denote the relative rankings of $DGTW_{i,t}$ and $AdjSUE_{i,t}$ as $Rank_{i,t}^{DGTW}$ and $Rank_{i,t}^{AdjSUE}$, respectively, and define REG as the difference between the two ranks:

$$REG_{i,t} = \frac{Rank_{i,t}^{DGTW} - Rank_{i,t}^{AdjSUE}}{(1{,}000 - 1) + (1{,}000 - 1)}. \tag{3}$$

For ease of interpretation, REG is normalized by the number of bins minus one, such that its potential values range from -0.5 to 0.5. Thus, a one-unit change in REG from -0.5 to 0.5 implies a flip from the most negative market reaction to the most positive market reaction, relative to the earnings surprise.

For robustness, we also consider alternative specifications of REG based on the relative rankings of (i) raw returns ($RET_{i,t}$) and unadjusted earnings surprises ($SUE_{i,t}$) or (ii) weekly and monthly abnormal returns ($DGTW_{i,t:t+4}$ and $DGTW_{i,t:t+21}$) and adjusted earnings surprises ($AdjSUE_{i,t}$), and we show in Section 4.3 that these specifications yield similar results. We focus on the one-day return response in our baseline analysis since it is highly visible, captures the attention of market participants, and is directly tied to earnings, while longer-horizon returns are confounded by other events that may occur.[6]

2.2 Analyst Expectations, Corporate Variables, and Control Variables

A main objective of this paper is to investigate how the non-fundamental component of earnings-day returns feeds back into the expectations formation of market participants. Our

[5] Our results are robust to using alternative numbers of bins. For example, Internet Appendix IA.5 shows that using 100 bins yields virtually identical results.

[6] As common in the literature, we shift earnings announcements that occur after the market close to the next day. According to Michaely et al. (2014), the available time stamps are very accurate and result in very few misclassification errors at a daily frequency.

baseline analysis focuses on institutional investor trading data from ANcerno[7] and on analyst earnings forecast errors (AFE) in line with the majority of the literature.[8] We obtain information on analysts' quarterly EPS forecasts from the I/B/E/S database. The analyst forecast error (AFE) is the difference between the median of analysts' EPS forecasts and the actual EPS, scaled by the standard deviation of analysts' EPS forecasts. Note that, by construction, the value of AFE is exactly opposite to that of SUE for each stock i on earnings announcement day t.[9]

When analyzing the relation of REG to corporate variables, we follow the literature and consider the 11 variables selected by Stambaugh et al. (2012, 2015). These variables capture both management actions and firm performance and correspond to well-known return anomalies. Like Stambaugh et al. (2012, 2015), we construct cross-sectional mispricing scores based on these characteristics. Each month, stocks are ranked based on the value of each characteristic, where a higher ranking means that the degree of overvaluation according to the related anomaly is greater, leading to negative subsequent returns. The ranking scores range from 0 to 100, where 100 captures overvaluation (i.e., the short leg). Averaging a stock's ranking scores across all characteristics provides us with its composite SYY mispricing score.

[7] ANcerno Ltd. (also known as Abel Noser) is a well-known consulting firm advising institutional investors regarding their transaction costs. We obtain their institutional trading dataset, which includes all trades made by ANcerno's clients, primarily mutual funds and pension plans. A detailed description of this dataset is provided in the appendix of Puckett and Yan (2011).

[8] In Internet Appendix IA.6.1 and IA.6.2, we provide further evidence exploring other dimensions of analyst estimate outputs that reflect analyst expectations: price target forecast errors (i.e., the implied return forecast errors, *RetForeErr*) and buy-and-sell recommendations changes (*RecChng*). Analyst 12-month price target estimates and buy-and-sell recommendations are obtained from the I/B/E/S database.

[9] While AFE is the negative value of SUE, both variables represent expectations or information at different points in time in our analysis. This is illustrated by the timeline in Internet Appendix Figure IA.1 for two subsequent earnings announcements. In our analysis, we use the SUE in quarter q for the construction of REG in quarter q, and our results show that quarter-q REG predicts AFE in quarter $q+1$ and subsequent quarters.

Finally, we construct the set of firm control variables used in our analysis using information from both the CRSP and I/B/E/S databases following the standard literature. We employ daily and monthly control variables depending on the frequency of the dependent variable. For example, SYY is observed on a monthly basis. Therefore, in the analysis of SYY, the daily firm control variables are recorded at the end of each month instead of end-of-day. The list of control variables and their explanation is provided in Internet Appendix Table IA.1.

2.3 Sample and Descriptive Statistics

Our sample period runs from 1985 to 2018, where the start of the sample is determined by the availability of analyst forecast data in the I/B/E/S database and the fact that we require one year of historical data for the construction of REG. We match the I/B/E/S tickers to CRSP using the ICLINK table and keep firms with valid links, and we furthermore utilize the standard CRSP/Compustat link. Our analysis of anomaly scores and corporate variables relies on infrequently updated accounting information. To reduce noise and have better consistency across firms' information sets, we focus on firms with a standard December fiscal year end.[10] Our final sample includes 228,266 earnings announcements for 8,434 distinct firms on 6,531 trading days between January 1985 to December 2018. On average, we have 35 distinct stocks with earnings announcements reported on an ordinary day in our sample.[11]

[Table 1]

[10]We obtain similar results without this restriction regarding the fiscal year, see Internet Appendix Table IA.11.

[11]The availability of dependent and control variables and requiring at least five degrees of freedom in daily Fama-MacBeth regressions leads to a varying number of observations across our tests. The effectively used maximum number of observations is 225,160 (see Table 2). In other tables, the number of observations is further reduced due to the availability of other variables, such as SYY mispricing scores or institutional trading data.

Table 1 provides descriptive statistics of our main variables. Panel A presents the time-series average of daily cross-sectional mean, standard deviation, and different quantiles for each variable. REG's average is around zero with a standard deviation of 0.172. The average daily $DGTW$ abnormal return is centered around zero as well. SUE (AFE) exhibits a positive (negative) average of 0.193 (-0.193), consistent with Mendenhall (2004). The average SYY score is around 50.

Panel B of Table 1 reports the time-series averages of daily cross-sectional correlations. The positive correlation of 0.211 between SUE and $DGTW$ shows that investors tend to respond in the same direction as the sign of the earnings surprise. However, the correlation is far from perfect, which is a known fact from the literature that motivates our analysis of the *gap* between both variables, captured by REG. Not surprisingly, REG is positively correlated with $DGTW$ and negatively correlated with SUE, but the correlations of 0.514 and -0.436 also clearly indicate that REG's relative ranking contains relevant information beyond the mere values of $DGTW$ and SUE. As we show in the next sections, REG is associated with an important non-fundamental component of earnings-day returns, complementing and contrasting with the well-studied fundamental component associated with SUE.

3 *REG* and the Long-Term Return Reversal

We document the striking result that earnings-day returns associated with REG are large in magnitude, revert subsequently to a large extent, and the reversal is very slow and takes about 3 years. To start with, we present evidence based on portfolio sorts. We rank stocks into deciles based on their REG on earnings day t, and compute equal-weighted DGTW-adjusted abnormal returns of each decile portfolio with a holding period from day $t+1$ to $t+n$

($n = 21, 63, 126, 252, 504$, and 756). In addition, we construct high-minus-low portfolios that go long stocks in the top decile and short stocks in the bottom decile. The returns are reported in Panel A of Table 2.

[Table 2]

A long-short portfolio based on day-t *REG* is associated with a DGTW-adjusted abnormal return of 10.40% on day t. Note that while a positive return on day t is expected by the construction of *REG*, both its magnitude and, importantly, whether it is followed by continuation or reversal in the subsequence are open empirical questions. We observe a reversal of around one tenth (1.03%/10.40% = 9.92%) of the day-t return over the subsequent 21 trading days. Strikingly, over longer horizons of up to one (three) years, the reversal becomes more pronounced and is on average 21.39% (54.45%) of the day-t return.

The observed long-term reversal for portfolios formed based on *REG*, the disparity between earnings-day returns and earnings surprises, is in stark contrast to the well-studied post-earnings-announcement drift (PEAD), which is captured by portfolios formed based on either the earnings-day return or the earnings surprise (Doyle et al., 2006; Livnat and Mendenhall, 2006). We confirm that the PEAD is present in our sample by reporting the related portfolio returns in Internet Appendix Table IA.2. The results show a pronounced PEAD for both the *SUE*-based and the *DGTW*-based portfolios, with the drift being substantially more pronounced when using the earnings surprise as a signal. Figure 1 illustrates the cumulative returns of these two portfolios compared to the portfolio formed based on *REG*, highlighting the long-term reversal associated with *REG* in direct contrast to the PEAD. Our findings show that while stock prices tend to underreact to the fundamental information on earnings days, followed by a drift, the gap between earnings-day returns and earnings surprises captures a substantial separate non-fundamental component, which slowly reverts over time. Our *REG* measure allows to capture and characterize this non-fundamental component, which is thus far not systematically studied in the literature.

We corroborate the portfolio-based results by running cross-sectional Fama-MacBeth regressions of future cumulative $DGTW$ abnormal returns on *REG*. We control for the two components of *REG*, i.e., SUE and $DGTW$, and also include a set of firm-level controls. The results reported in Panel B of Table 2 show that after the inclusion of various controls, the impact of *REG* on future cumulative abnormal returns remains strongly negative and significant, consistent with the portfolio-based results. The regressions confirm that there exists a pronounced long-term return reversal in response to *REG*, highlighting the slow correction of *REG*'s initial effect.

The long-term reversal of returns associated with *REG* suggests that the initial returns are subject to a bias in the market's reaction to earnings information, which gets slowly corrected afterwards. This result immediately motivates the question to what extent the biased price signal influences the expectation formation of other market participants going forward.

4 *REG*, Expectation Formation, and Mispricing-Related Corporate Variables

We show that *REG* feeds back into and distorts market participants' expectations formation, consistent with the observed long-term reversal. In particular, *REG* is an important predictor for the formation of biased expectations, as reflected by institutional trading, analyst forecast errors, and mispricing-related corporate variables. Section 4.1 shows that *REG* is followed by abnormal institutional trading in the same direction on the days after the announcement, and it significantly predicts analyst forecast errors up to 12 quarters ahead. In Section 4.2, we find that *REG* strongly positively predicts Stambaugh et al.'s (2015) composite scores (*SYY*) that are associated with mispricing. Exploring *SYY*'s individual characteristics, our results reveal that *REG* positively predicts management variables, such as stock issuances and investments, while it predicts disappointment in performance at the same time, as captured by lower return on assets (ROA) and lower gross profitability. Section 4.3 summarizes various additional tests and robustness checks of our main results on *REG* and expectation formation.

4.1 REG*, Institutional Trading, and Analyst Forecast Errors*

We investigate the predictive relation of *REG* to future expectations of market participants based on two main variables: net buying by institutional investors and analyst forecast errors. Importantly, the timing of our variables is such that *REG* is fully determined on earnings day t in quarter q (based on the released earnings information, the analyst forecasts for this quarter, and the market response to earnings), and we predict institutional buying pressure in the days after t and analyst forecast errors in the next quarters starting at $q + 1$. Figure IA.1 in the Internet Appendix illustrates the timeline, particularly for the relation of *REG* and future analyst forecast errors.

4.1.1 REG *and Institutional Trading*

If *REG* captures market participants' beliefs, we expect to find a positive relation between *REG* and the abnormal trading activity of institutional investors (who tend to be the marginal investors) on the earnings announcement day t. Moreover, a continuation in abnormal institutional trading in the subsequent days would strengthen the evidence for a shift in market participants' beliefs associated with *REG*. Such a finding would particularly imply that observing the disproportionate market reaction captured by REG does not prompt institutional traders to trade in the opposite direction, and rather reinforces their trading in the direction of REG. Finally, if such trading behavior is driven by biases, we expect to observe a reversal in returns once the institutional trading pressure subsides, as confirmed in Section 3.

We analyze the relation between REG and institutional directional trading around earnings announcements using daily Fama-MacBeth cross-sectional regressions, where for each day t we consider the firms, indexed by i, that announce earnings on that day. Institutional directional trading ($InstDirTrd$) in a stock is defined as net shares bought by institutionals normalized by daily trading volume. We regress $InstDirTrd_{i,t+1:t+n}$ and $InstDirTrd_{i,t:t+n}$ on $REG_{i,t}$, analyzing both the predictive relation of REG to cumulative institutional directional trading on the subsequent n trading days ($n = 5, 10, 15, 20$) as well as the total effect including the earnings day t.

The predictive regressions are specified as follows:

$$\begin{aligned} InstDirTrd_{i,t+1:t+n} &= \gamma_{0,t} + \gamma_{reg,t} REG_{i,t} + \gamma_{sue,t} SUE_{i,t} + \gamma_{dgtw,t} DGTW_{i,t} \\ &\quad + \sum_{k=1}^{K} \gamma_{k,t} CONTROLS_{k,i,t} + \epsilon_{i,t}. \end{aligned} \tag{4}$$

Similarly, the regression for the total effect is obtained by using $InstDirTrd_{i,t:t+n}$ as the dependent variable instead. We control for the standardized unexpected earnings $SUE_{i,t}$ and the DGTW-adjusted daily abnormal return $DGTW_{i,t}$ to ensure that the measured effect is not driven by the components of REG individually. Furthermore, a number of additional firm-level controls ($CONTROLS$) are included in line with the literature.[12] We report value-weighted averages based on the daily number of cross-sectional observations in the second stage of the Fama-MacBeth procedure.

[Table 3]

The results, displayed in Table 3, confirm our intuition. First, column (1) indicates that *REG* is positively associated with institutional directional trading on the earnings announcement day. Second, we observe a strong continuation in institutional trading after the earnings day. In fact, *REG* significantly predicts institutions' directional trading on the days after the earnings announcement up to 10 days after, suggesting that institutional investors continue to be net buyers of stocks with positive *REG*. This evidence supports the argument that *REG* captures an update in investor beliefs, as institutional investors do clearly not revise their direction of trading after observing *REG*. It rather appears that *REG* reinforces the expectation formation of investors, resulting in additional abnormal trading activity.

4.1.2 REG *and Analyst Forecast Errors*

We next investigate whether *REG* translates to the expectation formation of analysts through the perspective of future analyst earnings forecast errors. If *REG* does not have a meaningful predictive relation to analyst forecast errors, this could imply that analysts do not update their expectations in response to the return-earnings gap, or that the updating does not lead to smaller or greater forecast errors on average. If, on the contrary, *REG* predicts future

[12] We control for the firms' log size (*LnSIZE*) and book-to-market ratio (*LnBM*), cumulative stock returns over the past week (*RET5*), month (*RET21*), and year (*MOM*), the stocks' realized volatility (*RVOL*) and Amihud (2002) illiquidity (*ILLIQ*), as well as the dispersion of analysts' earnings forecasts (*DISP*) and the log number of analysts issuing earnings forecasts for the firm (*NUMEST*). All variables in our analysis are described in detail in Internet Appendix Table IA.1.

analyst forecast errors, then this suggests that analysts update their expectations in response to the market reaction, and a positive relation would suggest that they take over a bias in investor beliefs as they incorporate the observed market reaction.

Similar to Table 3, we assess the effect of REG on analyst forecast errors (AFE) using daily Fama-MacBeth cross-sectional regressions based on day t's announcing firms.[13] In particular, we use REG on day t in quarter q to predict AFE over the subsequent quarters up to $q + 12$ (three years ahead). The regression specification takes the following form:

$$\begin{aligned} AFE_{i,q+n} &= \gamma_{0,t} + \gamma_{reg,t} REG_{i,t} + \gamma_{afe,t} AFE_{i,t} + \gamma_{dgtw,t} DGTW_{i,t} \\ &\quad + \gamma_{syy,t} SYY_{i,t} + \sum_{k=1}^{K} \gamma_{k,t} CONTROLS_{k,i,t} + \epsilon_{i,t}, \end{aligned} \tag{5}$$

where $AFE_{i,q+n}$ is the analyst earnings forecast error of stock i for the earnings announcement n quarters ahead ($n = 1, \ldots, 12$). $REG_{i,t}$, $AFE_{i,t}$, and $DGTW_{i,t}$ are the return-earnings gap, analyst earnings forecast error, and the DGTW-adjusted daily abnormal return of stock i on earnings announcement day t in quarter q. $SYY_{i,t}$ is the monthly Stambaugh et al. (2015) score in the month of the earnings announcement. We control for AFE and $DGTW$ to make sure that the measured effect of REG is not due to the persistence in analyst forecast errors or the impact of past returns, and we also control for SYY to account for the relation between the SYY score and analyst forecast errors documented in previous studies. We include the same set of firm-level controls as in Eq. (4) and report value-weighted averages based on

[13] We present results from daily cross-sectional regressions in line with our return and institutional trading regressions, considering a day as a natural unit of observation for earnings announcements. Nevertheless, repeating the empirical analysis using monthly or quarterly cross-sectional regressions, where all daily observations within a month or quarter are pooled together in the first stage, yields very similar results (see Internet Appendix Table IA.3).

the daily number of cross-sectional observations in the second stage of the Fama-MacBeth procedure.

[Table 4]

The results are presented in Table 4. In all regressions, the coefficients on REG are positive and significant, implying a positive impact of REG on future analyst earnings forecast errors. The strength of the predictive relation decays from quarter 1 to quarter 12, which is expected given that new information enters the analysts' forecasts as time proceeds, but REG's predictive power for AFE is nevertheless economically and statistically significant even 12 quarters ahead. Specifically, the coefficient on REG for predicting AFE one quarter ahead is 2.464 with a t-statistic of 11.93, and it is 0.979 with a t-statistic of 4.10 for predicting AFE 12 quarters ahead. In terms of economic magnitude, an interquartile change in REG (from its 25^{th} percentile to its 75^{th} percentile) leads to an increase in the next quarter's AFE by 0.559 ($= (0.114 - (-0.113)) \times 2.464$), which is around 21.10% ($= 0.559/(0.829 - (-1.820))$) of AFE's interquartile range.[14] These results are not driven by the persistence in AFE, which is controlled for and reflected by the positive relation between AFE in quarter q and AFE over the subsequent quarters.

Overall, our findings in this section provide evidence that the market (mis)reaction to earnings news significantly influences market participants' expectations going forward. Evidence from analyst forecast errors indicates that a market response with a great disparity to the fundamental earnings surprise distorts analysts' beliefs and is reflected by significantly greater future analyst forecast errors. An in-depth analysis of analysts' expectation formation in Section 6 reinforces this interpretation by showing that REG predicts future analyst forecast

[14] As a comparison, the effect of SYY, calculated in a similar way, amounts to 10.49% of AFE's interquartile range, implying that the impact of REG on next quarter's analyst earnings forecast errors is twice as large as that of the SYY score.

errors more strongly for analysts who respond very quickly after an earnings announcement as well as for those who have lower-quality private information and are thus more dependent on public signals.

4.2 REG *and Mispricing-Related Corporate Variables*

We next analyze the relation between REG and important corporate variables. We focus on the firm characteristics selected by Stambaugh et al. (2012, 2015), which include management and performance-related variables (Stambaugh and Yuan, 2017). These characteristics serve as the base for the Stambaugh et al. (2015) composite mispricing scores and have been found to be associated with anomaly returns.

4.2.1 REG *and* SYY *Composite Scores*

We start by analyzing the predictive relation of REG to Stambaugh et al.'s (2015) composite scores (SYY). We employ Fama-MacBeth regressions for predicting SYY in the months following each earnings announcement. Since SYY is observed at a monthly frequency, we aggregate all daily observations (based on REG) at the monthly level and run monthly cross-sectional regressions:

$$\begin{aligned} SYY_{i,m+n} &= \gamma_{0,m} + \gamma_{reg,m} REG_{i,m} + \gamma_{afe,m} AFE_{i,m} + \gamma_{dgtw,m} DGTW_{i,m} \\ &\quad + \gamma_{syy,m} SYY_{i,m} + \sum_{k=1}^{K} \gamma_{k,t} CONTROLS_{k,i,t} + \epsilon_{i,m} \end{aligned} \tag{6}$$

$SYY_{i,m+n}$ is the monthly Stambaugh et al. (2015) score observed n months ahead at the end of the month. $REG_{i,m}$, $AFE_{i,m}$, and $DGTW_{i,m}$ are the return-earnings gap, analyst earnings forecast error, and DGTW-adjusted abnormal return on earnings announcement day t in month m. $SYY_{i,m}$ denotes the SYY score of the month of earnings announcement day t in month m. Firm-specific controls are included in line with our analysis in Section 4.1 and recorded at the end of the month of the earnings announcement.[15] As before, we compute the observation-weighted time-series average of each slope coefficient.

[Table 5]

We predict SYY for 3, 6, 9, 12, 24, and 36 months ahead and report the regression coefficients in Table 5. The collective results clearly indicate that REG has a significant and positive predictive relation to the composite SYY scores. An interquartile change in REG results in a rise in SYY of 0.523 ($= (0.114-(-0.113)) \times 2.304$), which is around 3% of SYY's interquartile range. For comparison, the increase in SYY associated with an interquartile change in AFE results in 0.156 ($= (0.829 - (-1.820)) \times 0.059$), which is less than 1% of SYY's interquartile range. Thus, the effect of REG on SYY scores is over three times that of AFE. Given the large amount of evidence in the literature on the relation between AFE and SYY (e.g., Jacobs, 2016), this comparison establishes that the effect of REG on SYY warrants attention.

4.2.2 REG *and* SYY*'s Individual Characteristics*

Next, we analyze the predictive relation of REG to the individual firm characteristics underlying the SYY composite score. We repeat the regression from equation (6), with the dependent variable being each individual characteristic's cross-sectional ranking.

[Table 6]

[15] We include log size ($LnSIZE$) and book-to-market ratio ($LnBM$) as well as monthly variants of the cumulative return ($MRET$), momentum ($MMOM$), realized volatility ($MRVOL$), and Amihud (2002) illiquidity ($MILLIQ$) variables. Precise definitions of these variables are provided in Internet Appendix Table IA.1.

Table 6 reports the results. We find that REG positively predicts the scores of virtually all individual anomaly-related characteristics, with slight variations in the predictive horizon and statistical significance. Economically, the results particularly show that REG predicts significantly greater equity issues as well as increased investment and net operating assets up to four quarters (12 months) ahead, suggesting that managers respond to the market's optimism either intentionally (taking advantage of the optimism) or unintentionally (sharing the same optimism), consistent with evidence documented in Baker and Wurgler (2000), Arif and Lee (2014), and Gennaioli et al. (2016).

At the same time, we also find that REG predicts an increase in the ranking of firms' future distress, gross profitability, and return on assets scores. Importantly, a higher *ranking* for the latter two variables coincides with lower values, such that overall, these outcomes consistently reflect lower performance going forward.[16] In combination, our results suggest that managers act in line with the overly positive reaction of the market to earnings news, which, however, is accompanied by a deteriorating future performance.

The predictability of corporate variables through REG is meaningful in its own right, but also particularly relevant as the considered variables are connected to an increase in mispricing along the lines of Stambaugh et al. (2015), implying that they are associated with subsequent negative stock returns. Motivated by these results, we explore the relation between REG, SYY scores, and related anomaly returns in depth in Section 5.

[16]When constructing mispricing scores along the lines of Stambaugh et al. (2015), all characteristics are ranked in such way that they predict lower future returns. Since gross profitability, ROA, and momentum have a positive relation to future returns, they are ranked in reverse order (see Internet Appendix Table IA.4), such that an increase in the ranking means lower raw values. Internet Appendix Table IA.5 reports the predictive relation of REG to the firms' *raw* characteristics (instead of the cross-sectional rankings), confirming that REG negatively predicts gross profitability and return on assets.

4.3 Summary of Robustness Tests

We conduct a number of robustness tests of our main findings. In Internet Appendix IA.5 (Tables IA.6–IA.11), we demonstrate that our results do not critically hinge on particular details of the measure construction approaches, the sample selection, or the research design. In particular, we show that our results are robust to variations in how we construct *REG*. They also hold for various sub-samples, when using panel regressions, and regardless of whether we include *SUE* and *DGTW* (the components of *REG*) as additional controls, and whether or not we include firms with different fiscal year ends in our sample.

In Internet Appendix IA.6 (Tables IA.12–IA.13), we extend the analysis of *REG*'s impact on analyst expectations beyond analyst earnings forecast errors, and find that the effect is further supported by a positive predictive relation to analyst price targets and recommendation changes (as explored by Brav and Lehavy, 2003; Jegadeesh et al., 2004; Da and Schaumburg, 2011; Engelberg et al., 2020).

In Internet Appendix IA.7 (Tables IA.14–IA.17), we first rule out that the observed influence of *REG* on analyst forecast errors is explained by analysts reporting too optimistic expectations due to their own career concerns (see Hong and Kubik, 2003). We analyze both positive and negative *REG*s and find that the positive relation of *REG* to next-quarter's *AFE* is clearly present on both sides, implying that our results are equally driven by excessive analyst optimism (after positive *REG* realizations) and pessimism (after negative *REG*). Similarly, *REG*'s predictive relation to *SYY* scores is more pronounced on the positive side, but statistically and economically significant on both sides.

Second, we provide more evidence to show that *REG*'s effect on analyst forecast errors and mispricing scores is not driven by "soft" information or other additional fundamental information released on earnings days that is not captured by *SUE*. Controlling for soft information based on textual measures of the earnings calls' management and Q&A transcripts using the Loughran and McDonald (2016) dictionary does not affect our main findings. Our results are also not substantially affected when controlling for sales forecast errors in addition to earnings forecast errors and hold when conditioning on earnings guidance (see Section 6.3), which constitute the most important non-earnings information (see Hand et al., 2022).

5 *REG* and Divergence in Anomaly Returns

The fact that REG captures and predicts variables related to market participants' expectations, such as analyst forecast errors and Stambaugh et al. (2015) mispricing scores, strongly suggests an important role of REG for anomaly returns. In particular, it is well-known that there is a link between analyst forecast errors (AFE) and anomaly returns since the early findings by La Porta (1996), and Stambaugh et al. (2015) show that their SYY scores negatively predict future returns. We analyze in this section how REG interacts with these relations.

In Section 5.1, we examine how REG affects the negative predictive relation of composite SYY scores to future returns and find that REG can significantly and persistently distort the correction of firm mispricing. These dynamics are consistent with our central result from Section 3 that the initial effect of REG reverses only very slowly. In Section 5.2, we show that REG has a very similar effect on individual anomalies, while on the other side, we do not observe the same dynamics conditional on earnings-day $DGTW$ or SUE.

Our findings highlight the importance of REG in capturing investors' biased belief formation and extend the result of Engelberg et al. (2018), who show that unconditionally, the correction of mispricing is accelerated on earnings days. The REG measure particularly allows us to characterize cases and episodes where the arrival of public information, on the contrary, results in deviations from the correction path and the emergence and amplification of mispricing.

5.1 REG *and Anomaly Returns*

We analyze how REG interacts with the relation between SYY scores and returns. While there is generally an unconditional negative cross-sectional relation between SYY composite scores and future stock returns, we show that the realization of REG can distort this relation and delay the correction of anomaly-related mispricing.

To fix ideas, let us take a look at the case of a high SYY score (overvaluation) before an earnings announcement and a positive REG realization on the earnings announcement day. While the positive earnings-day return associated with REG could, in principle, be driven by fundamental information, our evidence from the previous sections suggests that this is not the case, as REG is associated with biased expectations and a slow subsequent reversal of the initial return. As such, we expect a positive REG to be associated with a deviation from the anomaly correction path on the earnings announcement day, which is at the same time followed by a delayed and stronger subsequent convergence, as prices should catch up and return to their fundamental values. Thus, we conjecture that the generally negative effect of SYY in month $m-1$ on subsequent stock returns is delayed (accelerated) when the realization of REG in month m is "against" ("with") the expected mispricing correction.

To test this, we first rank all firms into five quintiles based on their SYY scores as of the end of month $m-1$, where $Q5$ indicates the greatest extent of overvaluation and $Q1$ implies the greatest extent of undervaluation. Unconditionally, high mispricing scores ($Q5$) generate negative returns in the subsequent month(s) and low mispricing scores ($Q1$) yield positive subsequent returns. Therefore, a long-short portfolio ($Q5-Q1$) generates significantly negative returns in line with the correction of mispricing, as the first three rows of Table 7 confirm.

Next, to capture REG's effect on the correction of mispricing in a systematic way, we construct two long-short portfolios conditional on the realization of REG, where REG is "against" or "with" the expected direction of the correction path. The "against portfolio" takes a long position in stocks with high SYY scores and positive REG and a short position in stocks with low SYY scores and negative REG, such that the realization of REG in month m is against the mispricing correction as prescribed by the SYY signal. In a similar manner, we construct the "with portfolio", which takes a long position in stocks with high SYY scores and negative REG and a short position in stocks with low SYY scores and positive REG. For this portfolio, the realization of REG in month m is in the direction of the mispricing correction as prescribed by the SYY ranking. We track the performance of these two long-short portfolios for 36 months and analyze how the realization of REG affects the general relationship between SYY and subsequent stock returns, where we report the returns with and without the contemporaneous effect of REG in month m.

[Table 7]

Table 7 presents the portfolio returns for different horizons. By construction, the "with portfolio" starts with a large negative return of −3.77% in the direction of mispricing correction, while the "against portfolio" works in the opposite direction with an initial return of 2.66%. In the subsequence, the cumulative returns of the "with portfolio" first further decline and then reach a steady state at around 12 months, while the cumulative returns of the "against portfolio" remain positive until 3 months horizon, turn negative after 6 months, and keep continually declining after that. Remarkably, the difference between the two portfolio returns, which is by construction large at 6.43% and highly statistically significant in the initial month, narrows continually to 1.86% after 36 months, at which point it is statistically indistinguishable from zero. These results, in line with our findings in the previous sections, are clear evidence of *REG* introducing biases into the market that are corrected afterwards. However, the correction is slow, and the gap created by the one-day return associated with *REG* starts closing only over a horizon of 2–3 years.

We corroborate these results by considering the rates of correction for the long-short portfolios, that is, the cumulative returns starting from month $m + 1$, excluding the contemporaneous effect of *REG*. Up to a 3-month horizon, the correction of the "with" and "against" portfolios has the same speed, and the returns are statistically indistinguishable, implying that a deviation from the correction of mispricing due to *REG* fully persists for 3 months. After that, the "against portfolio" shows a much stronger rate of correction which accumulates to a return of -6.93% after 36 months, while the "with portfolio" drops to -2.85% at a horizon of 12 months and roughly remains at this level. The much stronger correction rate for the "against portfolio" at longer horizons eventually undoes the initial earnings-day return against the direction of mispricing correction.

[Figure 2]

We illustrate the cumulative returns of the considered "with" and "against" portfolios in Figure 2. Panel (a) shows the portfolio returns, including the initial earnings-day effect due to *REG*, which by construction start with a pronounced gap, then gradually converge, and eventually arrive at nearly the same level. Panel (b) demonstrates the correction rates given by portfolio returns starting at month $m + 1$, which are initially indistinguishable in line with the slow correction, and considerably diverge over longer horizons.

5.2 Individual Anomalies and Comparison to DGTW and SUE Portfolios

We further illustrate the cumulative returns of the long-short portfolios at different horizons for three selected anomalies: "Composite Equity Issues", "Investment to Assets", and "Gross Profitability" (see also Internet Appendix Table IA.18). Panels (a), (b), and (c) of Figure 3 present the results for the related "against" and "with" portfolios. For all three anomalies, we observe very similar return patterns that confirm the effect of REG considerably delaying or accelerating the correction of mispricing, in line with our results on portfolios formed based on composite SYY mispricing scores.

[Figure 3]

Finally, we investigate whether the obtained results are specific to REG, or if we are able to capture the same effects by conditioning on abnormal earnings-day returns, $DGTW$, or on earnings surprises, SUE. Panels (a) and (b) of Figure 4 present the anomaly returns conditional on $DGTW$ and SUE, respectively, in direct analogy to Figure 2. It is striking that for both $DGTW$ and SUE, the cumulative return spread between the "against" and "with" portfolios widens with the investment horizon, rather than narrowing and disappearing. For $DGTW$, the initial gap in month m is 14.86%, and it extends to 17.74% over the subsequent 36 months. For SUE, the initial gap of 12.04% widens to 18.55% over 36 months.[17]

[Figure 4]

It is thus evident that returns associated with the $DGTW$ or SUE signals "against" the direction of mispricing correction are not reversed afterward, suggesting that both signals are dominated by new fundamental information. In contrast, the gap between returns and

[17] Internet Appendix Tables IA.19 and IA.20 present the tabulated performance figures for these portfolios.

earnings surprises measured by REG is indicated to be largely driven by bias, and the associated returns "against" the correction of mispricing are slowly reversed. In combination, our tests confirm that REG captures unique and relevant information for anomaly returns, which is consistent with biased expectations that drive anomaly returns further away from convergence for an extended period of time.

6 *REG*, Expectation Formation, and the Information Environment

The results presented in the previous sections reveal the non-fundamental role of earnings days, highlighting how REG persistently affects and distorts market participants' expectations and market outcomes. Providing a more detailed perspective on the mechanism, we finally examine how the effect of REG on analyst expectations and management decisions varies with the information environment. First, we show that future analyst forecast errors are more strongly affected by REG for analysts reacting rather promptly after the earnings announcement. Second, we find a stronger reaction of AFE to REG for analysts with less private information, as reflected by a lower industry concentration or a lower past forecast accuracy. This channel is further confirmed by utilizing the Global Analyst Research Settlement, a one-time quasi-exogenous event causing a negative shock to the analysts' information set. Third, we find that the relation between REG and SYY scores is more pronounced for firms with poorer information quality, i.e., firms without earnings guidance and firms with higher earnings volatility. Fourth, we provide evidence of an amplification between REG and other market participants' expectations. We show that REG's effect on analyst expectations is more pronounced if it confirms pre-existing biases (in line with, e.g., Pouget et al., 2017). In addition, *REG*'s effect on mispricing-related corporate variables is as well amplified if it goes in the same direction as pre-existing analyst biases (for example, when analysts are overly optimistic, but the market reaction to the underwhelming earnings surprise is disproportionately positive).

Overall, these findings extend the predictability results from Section 4 and strengthen the evidence for a direct effect of the non-fundamental component of earnings-day returns on market participants' expectations.

6.1 REG*'s Effect on Analyst Expectations – Promptness*

We analyze to what extent *REG*'s predictive relation to future analyst forecast errors varies with the promptness with which analysts update their expectations after the earnings announcement. Analysts have incentives to provide accurate forecasts but also want to react quickly to provide updated information to their clients (Chiu et al., 2021). We hypothesize that *REG* predicts future forecast errors more strongly for analysts who react more quickly and are thus more prone to be affected by the potentially biased signal.

We classify *individual* analyst earnings forecasts for quarter $q+1$ that are issued after the earnings announcement of quarter q based on their timeliness after observing the earnings announcement and market reaction (*REG*). If a forecast was issued within ten days after quarter q's earnings announcement (within the interval $[t{+}1{:}t{+}10]$), it is assigned to the group $Promptness = 1$. Similarly, we define the promptness groups 2, 3, and 4 for forecasts issued during the time intervals $[t{+}11{:}t{+}30]$, $[t{+}31{:}t{+}60]$, and after $t{+}60$ relative to the earnings announcement. We compute the average analyst forecast errors for each of the four groups, $AFE^{Promptness=k}$ ($k = 1, 2, 3, 4$), and repeat the daily Fama-MacBeth cross-sectional regression (5) as defined in Section 4.1.2 for each separate group.

[Table 8]

Table 8 reports the results for each of the four promptness groups. We first observe that the coefficients on REG are consistently positive and statistically significant across all four groups, which resonates with our main findings based on the I/B/E/S consensus that aggregates all forecasts. At the same time, the results also reveal that REG predicts next-quarter AFE most strongly for those analysts who revise their forecasts very shortly after the earnings announcements and corresponding market reaction, i.e., $Promptness = 1$. The magnitude of coefficients, as well as their t-statistics, decline monotonically as we move towards the group $Promptness = 4$, which represents analysts updating their forecasts long after the earnings day. These results show that analysts who update their forecasts quickly after an earnings announcement are more strongly influenced by REG than those who issue their new forecast later and are thus not under the immediate impression of the market reaction on the earnings day.

6.2 REG*'s Effect on Analyst Expectations – Quality of Private Signals*

Next, we explore the heterogeneity in analyst characteristics related to the quality of their private signals. The intuition is that analysts with weaker private signals should be more strongly influenced by the public information conveyed through REG. In particular, we focus on two analyst-specific variables: (i) the degree of analyst industry concentration (analogous to Kacperczyk et al. 2005 for mutual fund managers), as measured by the number of industries covered by an analyst in a given quarter ($NumInd$), and (ii) an analyst's past stock-level forecast accuracy, captured by Clement's (1999) $PMAFE$ (Proportionate Mean Absolute Forecast Error) measure over the past four quarters. Past forecast accuracy can be viewed as a "catch-all" proxy for analyst ability, experience, or the attention paid by the analyst to the stock. We rank each analyst in a given quarter based on a decile ranking of these two variables.

We interact REG with these analyst characteristic rankings and predict future analyst forecast errors using a panel regression at the stock-analyst-quarter level, extending our baseline specification in Section 4.1.2:

$$\begin{aligned} AFE_{j,i,q+n} &= \gamma_0 + \gamma_{reg} REG_{i,q} + \gamma_{rank} Rank(Char)_{j,i,q} \\ &\quad + \gamma_{reg\_rank} REG_{i,q} \times Rank(Char)_{j,i,q} + \gamma_{afe} AFE_{j,i,q} \\ &\quad + \gamma_{dgtw} DGTW_{i,q} + \gamma_{syy} SYY_{i,q} + \sum_{k=1}^{K} \gamma_k CONTROLS_{k,i,q} + \epsilon_{j,i,q} \end{aligned} \tag{7}$$

$AFE_{j,i,q+n}$ is analyst j's earnings forecast error (AFE) for stock i for the earnings announcement n quarters ahead ($n = 1, \ldots, 4$) based on the analyst's most recent forecast before the upcoming earnings announcement, and $Rank(Char)$ is the decile ranking of the considered characteristic ($NumInd$ or $PMAFE$). The other variables are defined as before, and we include the standard set of controls for firm characteristics as in Section 4.1. In addition, we control for the number of days between the analyst's earnings forecast and the firm's earnings announcement. The panel regressions include analyst and quarter fixed effects, and standard errors are clustered by analyst and quarter.

[Table 9]

The results in Table 9 show that greater industry concentration results in a smaller response of AFE to REG. That is, analysts who focus on a smaller number of industries are less sensitive to the market's reaction, consistent with the idea that more industry-concentrated analysts can generate higher-quality private signals and are thus less influenced by the market response when updating their beliefs.[18] Similarly, we find that analysts with lower past stock-level forecast accuracy (that is, higher $PMAFE$) are more affected by REG. It is important to note that stock-level forecast accuracy does not govern—ex-ante—the direction of the response to REG, as a lack of accuracy can be driven by either a positive or a negative bias.

Overall, REG's impact on expectations is more pronounced for analysts who are less focused on a specific industry and who demonstrate lower past forecast accuracy. These results suggest that analysts who do not have strong private information are more prone to be influenced by the non-fundamental component of earnings-day returns. We further confirm this intuition by utilizing the Global Analyst Research Settlement (GS), a one-time quasi-exogenous event causing a negative shock to the analysts' information set (see Internet Appendix IA.9 for more details).[19] In this test, we show that analyst forecast errors for firms with more GS-affected analysts respond much more strongly to REG after the Global Settlement took effect, while no such difference is observable for firms with a small number of GS-affected analysts. This change is reflective of an increase in GS-affected analysts' reliance on public signals when their access to information via the investment banking department is restricted as a result of the GS.

6.3 REG*'s Effect on* SYY *Scores – Firm Information Environment*

In a similar spirit, we consider the relation between REG and SYY mispricing scores conditioning on the firm information environment. Motivated by the results for analyst

[18]For example, a change from a rank of 1 to 10 in industry concentration results in an additional response of AFE to REG of $0.101 \times 9 = 0.909$, which is 50% larger than the baseline result.

[19]The Global Settlement event has attracted great interest among researchers, with several papers analyzing its general effects. For instance, Kadan et al. (2009) find that after the GS, the overall informativeness of analyst recommendations has declined, in line with reduced access to private information. Corwin et al. (2017) show that the GS has led to a decline in analyst affiliation bias for GS-affected institutions.

expectations, we hypothesize that this relation should be stronger for firms with a poorer information environment. To explore this idea, we revisit the relation between *REG* and *SYY* scores using cross-sectional subsamples based on (i) the availability of earnings guidance and (ii) the firms' earnings volatility being above or below the cross-sectional median.

[Table 10]

We estimate the Fama-MacBeth regression from equation (6) for these subsamples and report the results in Table 10. The first set of results indicates that earnings guidance is relevant for the cross-sectional relation between *REG* and *SYY*, with the effect being significantly more pronounced for firms without earnings guidance. For example, 3 months ahead, firms without earnings guidance exhibit an 83% (= 0.998/1.201) higher sensitivity of *SYY* scores to *REG*. The difference becomes even larger for longer horizons. We find a similar effect for the subsamples based on earnings volatility, with a higher earnings volatility yielding a more pronounced effect of *REG* on *SYY* scores. For a horizon of 3 months, firms with above-median earnings volatility exhibit a 97% (= 1.438/1.487) higher sensitivity of *SYY* scores to *REG*.

Altogether, these results show that *REG* predicts corporate variables associated with mispricing (as captured by *SYY* scores) more strongly for firms with a poorer information environment. In Internet Appendix Table IA.22, we consider additional subsamples based on analyst coverage, firm size, institutional holdings, and analyst disagreement, and the results are consistent with this conclusion. In sum, all these findings support the view that economic agents react more strongly to the non-fundamental component captured by *REG* when their other signals are rather weak.

6.4 REG*'s Effect on Analyst Expectations and* SYY *Scores – Confirmation Bias and Amplification Effect*

Rounding off this section, we finally demonstrate that the impact of REG on market participants' expectations exhibits features of a "confirmation bias", as proposed by Pouget et al. (2017), Hirshleifer et al. (2021), and Cookson et al. (2023). Precisely, we show that analysts are more strongly affected by the REG signal if it confirms their current (biased) views as reflected by their contemporaneous forecast errors (AFE). In a similar manner, the predictive relation of REG to corporate variables is amplified when investors and analysts share the same biases, that is, when REG and AFE are in the same direction.

We capture the hypothesized confirmation and amplification effect by defining a dummy variable D(Amplification)=D(AFE_q & REG_q Same Sign), which is equal to one if REG in a given quarter q is in the same direction as AFE for that quarter. For example, the dummy variable is equal to one in a case where the analysts' prior expectations are overly optimistic, such that the realized AFE is positive, and a relatively positive market reaction (to the lower-than-expected earnings) confirms their expectations.

We first analyze whether the next quarter's AFE has a higher likelihood of being in the same direction as current AFE when current AFE and REG are in the same direction. To test this hypothesis, we broadly follow Pouget et al. (2017) and employ a linear probability model, regressing the dependent dummy variable D(AFE_q & AFE_{q+n} Same Sign) on the main explanatory variable D(AFE_q & REG_q Same Sign) and additional control variables. The precise regression specifications estimated in this section are described in Internet Appendix IA.11. The results in Table 11 show, indeed, that when the disproportionate market reaction (REG) is in the same direction as the analysts' initial bias (AFE), analysts will view this as a confirmatory signal. As a result, we observe a higher likelihood of a continuation of the bias in these cases. The coefficient estimate in column (1) is 0.127, which indicates that in the subsequent quarter, analysts will have a 12.7% higher probability of issuing a forecast that is biased in the same direction as their current forecast if *REG* provides confirming information. Notably, the persistence of *AFE*, measured in a similar way by the dummy D(AFE_q & AFE_{q-1} Same Sign), is associated with a probability of 20.8%, showing that our confirmation effect is economically significant.

[Table 11]

Second, we ask whether the predictive relation of *REG* to corporate variables established in Section 4.2 is, similarly, more pronounced when analyst biases are confirmed by the market reaction. The idea is that if analysts are optimistic about the stock and market participants respond in the same direction, suggesting that both groups are aligned, then the impact of *REG* on corporate actions (as captured by SYY scores) should be larger. We repeat regression (6), including the D(Amplification) variable as well as its interaction with *REG*, and report the results in Table 12.

[Table 12]

The coefficients in the first two rows of the table show that the positive impact of *REG* on future SYY scores is more strongly pronounced when there is an amplification between *REG* and *AFE*. While a higher *REG* predicts a greater SYY in the next quarter in a statistically significant way even without the amplification effect, the magnitude of *REG*'s impact with amplification ($\gamma_{reg,m} + \gamma_{reg\_amp,m} = 0.857 + 1.656 = 2.513$) is nearly three times as large as when amplification is absent ($\gamma_{reg,m} = 0.857$). Figure 5 plots the impact of *REG* on SYY for both cases. It is clearly visible that SYY is significantly positively affected by *REG* even in the baseline case, but the impact is much stronger when analyst forecast errors and the return-earnings gap are aligned. Overall, our findings in this section provide evidence for a confirmation bias when analysts learn from the *REG* signal, as well as an amplification of biases between analysts and investors in explaining future *SYY* mispricing scores. These findings motivate future research on the detailed interactions and amplification of biases between investors, analysts, and managers, both in the context of earnings days and in general.

[Figure 5]

7 Conclusion

How investors form their expectations and how their expectations drive asset prices has been in the interest of academic research over the last several decades. Recent research highlights cognitive and other constraints that lead to biased expectation formation.

In this paper, we provide new empirical evidence that enriches the current view in the literature. Using a new measure—*REG*— that captures investor (mis)reaction to cash flow information, we show that in contrast to the common fundamental view, earnings days can disseminate non-fundamental information and amplify existing biases. We show that 50% of the returns associated with *REG* reverse over a period of three years, which stands in stark contrast to the robust evidence of underreaction to earnings news for extreme *SUE* and extreme returns. Consistent with that, we are also able to reveal substantial heterogeneity in mispricing dynamics. While previous literature documents that, on average, the arrival of public information accelerates the correction of mispricing (e.g., Engelberg et al., 2018), we reveal that earnings announcement days can also contribute to the emergence and amplification of mispricing, providing a richer picture of investor beliefs and price dynamics.

We further show that market participants are likely to incorporate the (biased) signals revealed by other agents when forming their expectations. Consequently, the expectation formation across market participants is a dynamic process featuring feedback effects that can result in an amplification of agents' initial biases. In particular, we show that future analyst forecast errors are predicted by *REG*, and that this predictability is more pronounced when the market reaction to earnings confirms the analysts' prior views. We also show that the market's initial reaction to earnings predicts management actions that are associated with optimism (Gennaioli et al., 2016) and mispricing, such as stock issuance and investment.

To formalize the link between *REG* and the amplification of biases as well as the interpretation of these results, we present a simple structural model in which investors, as well as analysts and managers, dynamically update their expectations of the firms' earnings growth rate.

Overall, the dynamics that we document in this paper complement and contrast with the predominant fundamental view of earnings announcements in the literature. The rich dynamics in response to *REG* also contribute to the understanding of investors' belief formation and their effect on asset prices. In particular, they demonstrate the potential spillover effects in investors' expectation formation, which result in amplification effects. They also add to the ongoing debate on the source of anomaly returns. Future research should take these dynamics into account when assessing the interactions between agents' beliefs and asset prices.

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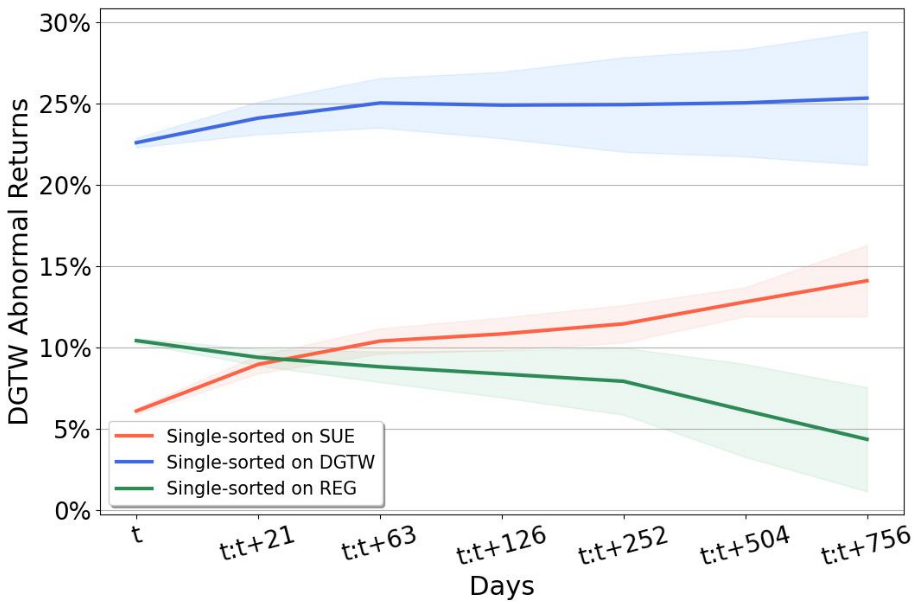
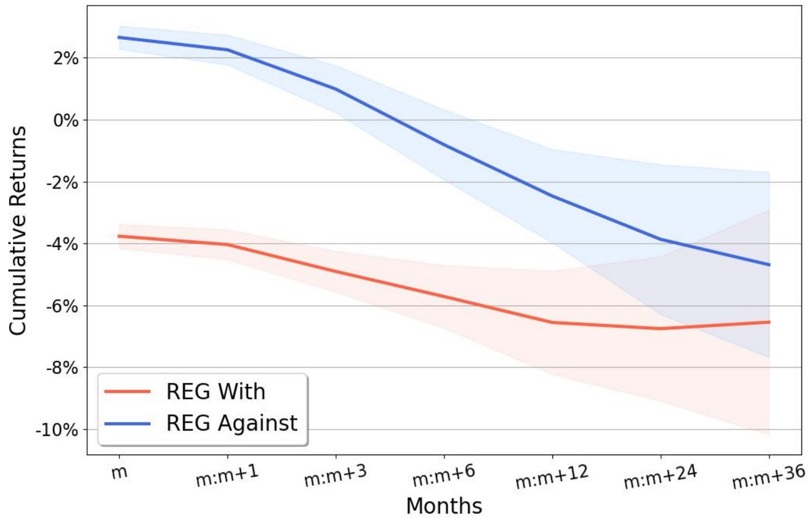
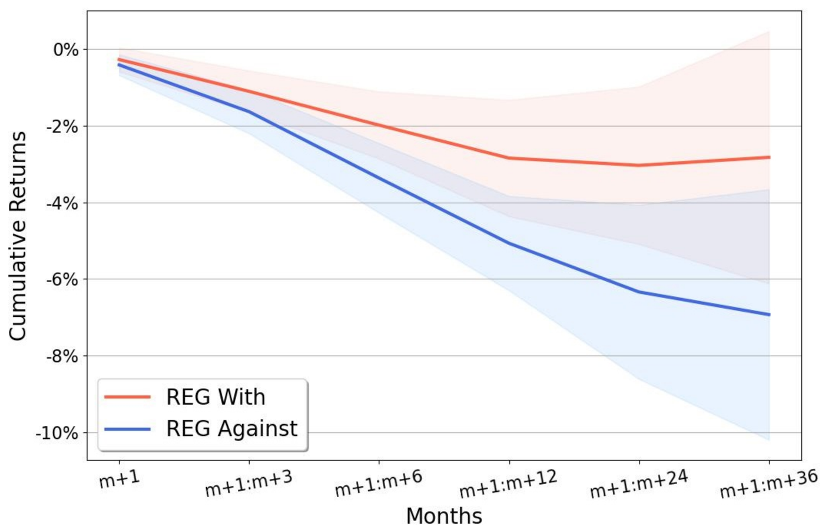


Fig. 1 – *REG*, *DGTW*, *SUE*, and Subsequent Abnormal Returns

The figure above presents the DGTW-adjusted abnormal returns of high-minus-low decile portfolios of stocks single-sorted on the return-earnings gap *REG*, on characteristic-adjusted earnings-day returns *DGTW*, and on earnings surprises *SUE*, respectively. Specifically, portfolios are formed on the earnings day t, and the figure illustrates the average DGTW-adjusted abnormal returns on day t as well as the cumulative DGTW-adjusted abnormal returns from day t to day $t+n$ ($n = 21, 63, 126, 252, 504, 756$), along with the corresponding 90% confidence intervals.



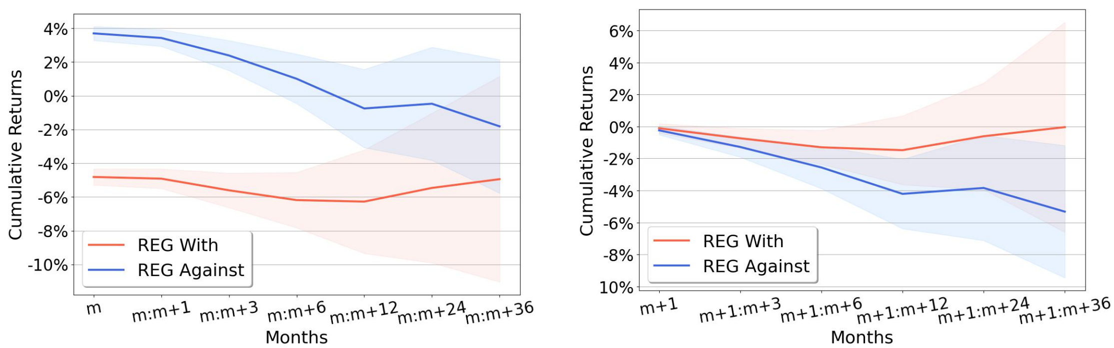
(a) From month m to month $m + n$



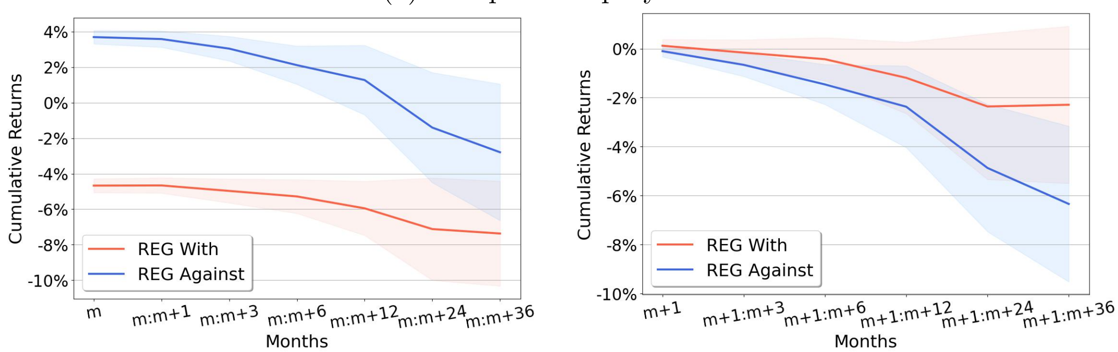
(b) From month $m + 1$ to month $m + n$

Fig. 2 – REG and Anomaly Returns

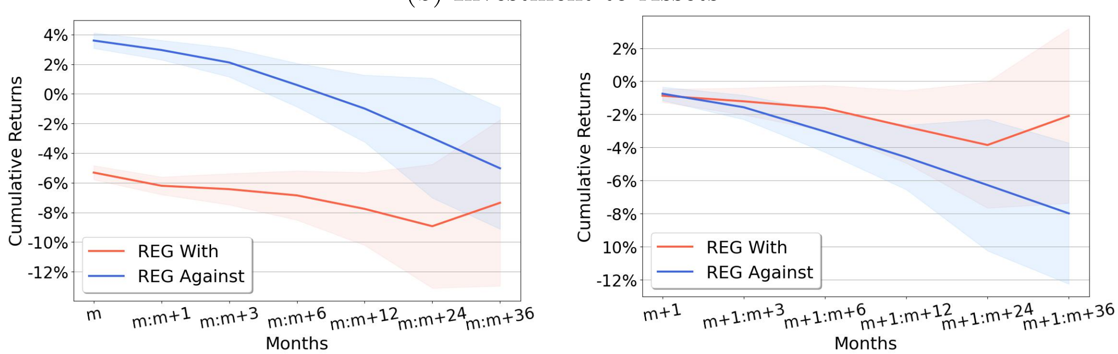
The figures above present the cumulative returns for two long-short portfolios formed based on SYY composite mispricing scores and REG, along with 90% confidence intervals. The "REG Against" portfolio takes a long position in stocks with SYY scores being in the top quintile in month $m - 1$ and a positive realization of REG in month m ($REG > 0$), and a short position in stocks with SYY scores being in the bottom quintile in month $m - 1$ and a negative realization of REG in month m ($REG < 0$). The "REG With" portfolio takes a long position in stocks with SYY scores being in the top quintile in month $m - 1$ and a negative realization of REG in month m ($REG < 0$), and a short position in stocks with SYY scores being in the bottom quintile in month $m - 1$ and a positive realization of REG in month m ($REG > 0$). Panel (a) shows the cumulative performance of the two portfolios starting from month m to $m + n$ ($n = 0, 1, 3, 6, 12, 24, 36$), and Panel (b) illustrates the cumulative returns starting in month $m + 1$.



(a) Composite Equity Issues



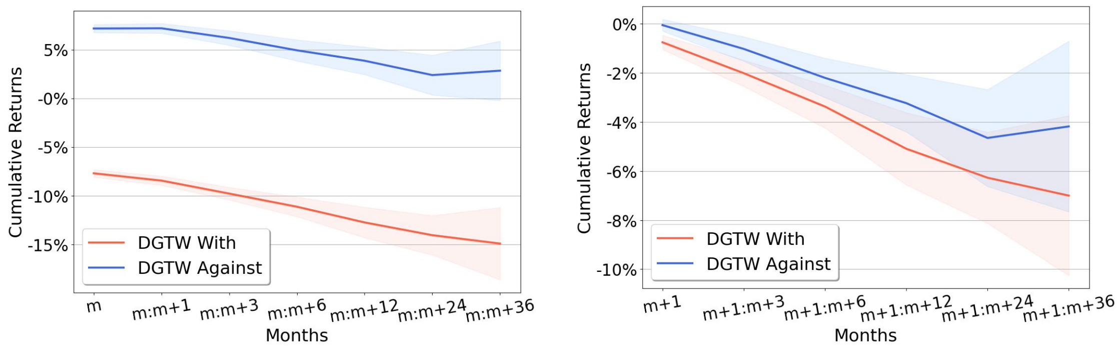
(b) Investment to Assets



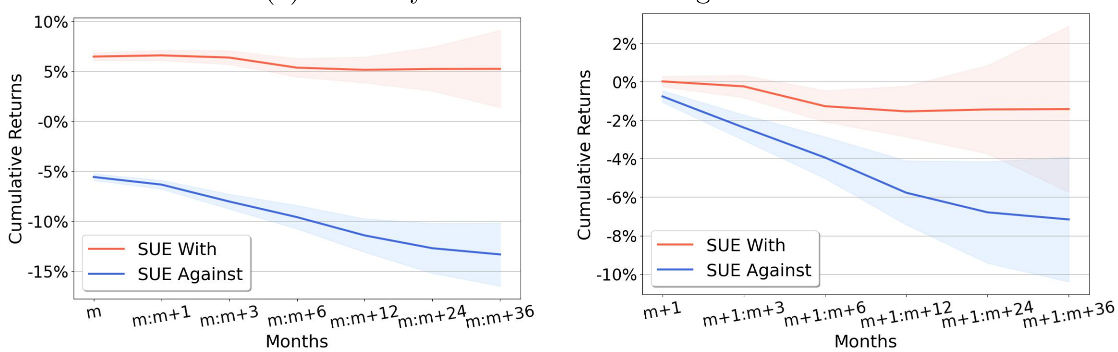
(c) Gross Profitability

Fig. 3 – *REG* and Anomaly Returns: Individual Anomalies

The figures above extend the analysis from Figure 2 to individual anomalies. In particular, the figure presents the cumulative returns for two long-short portfolios formed based on individual anomaly scores and *REG*, along with 90% confidence intervals. The "REG Against" and "REG With" portfolios are constructed as in Figure 2, where we replace the composite ranking with the individual anomaly ranking. Panels (a), (b), and (c) display the corresponding portfolio returns for the Composite Equity Issues, Investment to Assets, and Gross Profitability anomalies, respectively. Figures on the left show the cumulative performance of the long-short portfolios starting from month m to $m+n$ ($n = 0, 1, 3, 6, 12, 24, 36$), and figures on the right illustrate the cumulative returns starting in month $m+1$.



(a) Anomaly Returns Conditioning on $DGTW$



(b) Anomaly Returns Conditioning on SUE

Fig. 4 – Anomaly Returns Conditioning on $DGTW$ and SUE

The figures above present the cumulative returns for two long-short portfolios formed based on SYY composite mispricing scores and $DGTW$ (or SUE), along with 90% confidence intervals. Panel (a) presents the results for anomaly returns conditioning on $DGTW$, and Panel (b) displays the results for anomaly returns conditioning on SUE. In Panel (a), the "DGTW Against" portfolio takes a long position in stocks with SYY scores being in the top quintile in month $m-1$ and a positive realization of $DGTW$ in month m ($DGTW > 0$), and a short position in stocks with SYY scores being in the bottom quintile in month $m-1$ and a negative realization of $DGTW$ in month m ($DGTW < 0$). The "DGTW With" portfolio takes a long position in stocks with SYY scores being in the top quintile in month $m-1$ and a negative realization of $DGTW$ in month m ($DGTW < 0$), and a short position in stocks with SYY scores being in the bottom quintile in month $m-1$ and a positive realization of $DGTW$ in month m ($DGTW > 0$). In Panel (b), the "SUE With" portfolio takes a long position in stocks with SYY scores being in the top quintile in month $m-1$ and a positive realization of SUE in month m ($SUE > 0$), and a short position in stocks with SYY scores being in the bottom quintile in month $m-1$ and a negative realization of SUE in month m ($SUE < 0$). The "SUE Against" portfolio takes a long position in stocks with SYY scores being in the top quintile in month $m-1$ and a negative realization of SUE in month m ($SUE < 0$), and a short position in stocks with SYY scores being in the bottom quintile in month $m-1$ and a positive realization of SUE in month m ($SUE > 0$). Figures on the left show the cumulative performance of the two portfolios starting from month m to $m+n$ ($n = 0, 1, 3, 6, 12, 24, 36$), and figures on the right illustrate the cumulative returns starting in month $m+1$.

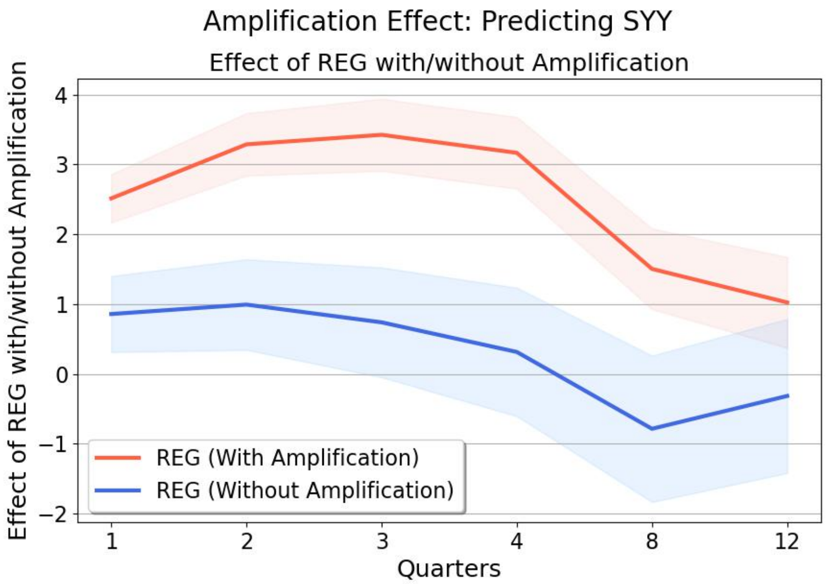


Fig. 5 – REG's Effect on SYY Scores: Amplification

The figure shows the impact of REG on SYY composite mispricing scores without amplification effect and the overall impact 1, 2, 3, 4, 8, and 12 quarters ahead, together with the corresponding 90% confidence intervals. In particular, we estimate Fama-MacBeth regressions of future SYY on REG and on the interaction of REG with an amplification dummy that equals one when REG and AFE are of the same sign in a given quarter. The blue line depicts the coefficient on REG as the effect without amplification, the red line the sum of this baseline effect and the coefficient on the interaction term.

Table 1 – Descriptive Statistics

This table reports descriptive statistics for the variables used in our analysis. Our sample consists of 8,434 distinct companies with analyst earnings forecasts and earnings information in the I/B/E/S database from January 1985 to December 2018. Panel A reports the observation-weighted time-series average of the daily cross-sectional mean, standard deviation, and quartiles of each variable. Panel B shows the observation-weighted daily time-series average of the cross-sectional correlations of our main variables. An overview of all variable definitions and descriptions is provided in Internet Appendix Table IA.1.

Panel A: Cross-Sectional Summary Statistics

	Mean	SD	P1	P25	Median	P75	P99
Main variables							
REG	0.000	0.172	-0.377	-0.113	0.001	0.114	0.372
SUE	0.193	5.348	-19.404	-0.829	0.421	1.820	12.785
DGTW	0.000	6.122	-17.757	-2.613	0.004	2.688	16.973
AFE	-0.193	5.348	-12.785	-1.820	-0.421	0.829	19.404
SYY	50.276	12.582	24.491	41.404	49.832	58.779	78.780
Institutional trading and alternative analyst expectation measures							
InstDirTrd	0.266	12.858	-42.334	-1.880	0.000	2.670	41.953
RetForeErr	17.719	46.308	-64.183	-12.336	12.056	44.444	119.348
$RecChng_{t+1:t+5}$	0.098	1.405	-2.000	-1.000	1.000	1.000	2.000
$RecChng_{t+6:t+15}$	0.177	1.423	-2.000	-1.000	1.000	1.000	2.000
Control variables							
LnSIZE	6.822	1.568	3.791	5.697	6.725	7.841	10.608
LnBM	-0.795	0.781	-3.044	-1.228	-0.706	-0.277	0.778
RET5	0.420	5.837	-13.649	-2.583	0.150	3.064	17.831
RET21	0.903	11.463	-26.672	-5.210	0.443	6.335	34.852
MOM	15.556	49.190	-60.433	-12.148	8.568	32.403	196.426
RVOL	0.416	0.234	0.124	0.263	0.362	0.508	1.248
ILLIQ	0.206	1.115	0.000	0.002	0.010	0.051	5.606

Panel B: Cross-Sectional Correlations of Main Variables

	REG	*SUE*	*DGTW*	*AFE*	*SYY*
REG	1.000				
SUE	-0.436	1.000			
DGTW	0.514	0.211	1.000		
AFE	0.436	-1.000	-0.211	1.000	
SYY	0.051	-0.097	-0.017	0.097	1.000

Table 2 – *REG* and Subsequent Returns

This table reports returns of portfolios formed based on *REG* as well as results from Fama-MacBeth regressions of returns for different horizons after the earnings announcement on *REG* and other variables. Panel A reports the average *DGTW* abnormal returns (expressed in percent) on the earnings day t and cumulative *DGTW* abnormal returns from day $t+1$ to day $t+n$ ($n = 21, 63, 126, 252, 504, 756$) of decile portfolios formed based on *REG* on day t, as well as of the corresponding high-minus-low (H-L) portfolio. The magnitude of reversal (Rev. Mgn.) as a percentage of the day-t effect is reported in the last column. Panel B reports the results from Fama-MacBeth cross-sectional regressions of cumulative *DGTW* abnormal returns from day $t+1$ to $t+n$ ($n = 21, 63, 126, 252, 504, 756$) on *REG* and other variables. The sample period is from January 1985 to December 2018. We report value-weighted time-series averages of the cross-sectional regression estimates based on the daily number of cross-sectional observations. t-statistics based on Newey-West standard errors are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Abnormal Returns of Single-Sorted Portfolios Based on REG

	Decile Portfolios Sorted by REG_t											
	Low	D2	D3	D4	D5	D6	D7	D8	D9	High	H-L	Rev. Mgn.
$DGTW_t$	-5.26***	-3.28***	-2.37***	-1.77***	-0.84***	0.71***	1.79***	2.55***	3.23***	5.14***	10.40***	
	(-95.97)	(-71.83)	(-55.51)	(-38.69)	(-14.84)	(14.19)	(41.67)	(56.28)	(66.17)	(95.91)	(115.47)	
#Obs	3,439	3,439	3,439	3,439	3,439	3,439	3,439	3,439	3,439	3,439	3,439	
$DGTW_{t+1:t+21}$	0.55***	0.27***	0.29***	0.23***	0.36***	0.24***	-0.09	-0.07	-0.41***	-0.48***	-1.03***	*-9.92%*
	(4.70)	(2.61)	(3.04)	(2.59)	(3.65)	(2.77)	(-1.10)	(-0.71)	(-4.56)	(-3.66)	(-6.65)	
#Obs	3,419	3,419	3,419	3,419	3,419	3,419	3,419	3,419	3,419	3,419	3,419	
$DGTW_{t+1:t+63}$	0.41*	0.08	-0.26*	-0.15	0.14	0.11	-0.28*	-0.43**	-0.93***	-1.11***	-1.51***	*-14.54%*
	(1.71)	(0.45)	(-1.66)	(-0.85)	(0.71)	(0.74)	(-1.88)	(-2.27)	(-5.36)	(-4.33)	(-5.30)	
#Obs	3,356	3,356	3,356	3,356	3,356	3,356	3,356	3,356	3,356	3,356	3,356	
$DGTW_{t+1:t+126}$	0.02	-0.13	-0.65***	-0.34	-0.23	-0.28	-0.61**	-1.06***	-1.52***	-1.80***	-1.82***	*-17.55%*
	(0.06)	(-0.47)	(-3.12)	(-1.06)	(-0.76)	(-1.02)	(-2.36)	(-3.21)	(-4.66)	(-4.01)	(-3.79)	
#Obs	3,273	3,273	3,273	3,273	3,273	3,273	3,273	3,273	3,273	3,273	3,273	
$DGTW_{t+1:t+252}$	-0.24	-0.65**	-1.24***	-0.84	-0.77*	-1.05**	-1.70***	-1.22**	-2.65***	-2.47***	-2.22***	*-21.39%*
	(-0.48)	(-2.00)	(-3.14)	(-1.38)	(-1.70)	(-2.49)	(-3.16)	(-2.21)	(-4.94)	(-3.42)	(-3.31)	
#Obs	3,122	3,122	3,122	3,122	3,122	3,122	3,122	3,122	3,122	3,122	3,122	
$DGTW_{t+1:t+504}$	0.14	-1.26*	-2.02**	-1.68*	-1.83**	-1.89**	-2.65***	-1.66*	-3.76***	-3.81***	-3.95***	*-38.04%*
	(0.12)	(-1.84)	(-2.36)	(-1.87)	(-2.33)	(-2.27)	(-2.86)	(-1.76)	(-4.87)	(-3.56)	(-3.60)	
#Obs	2,877	2,877	2,877	2,877	2,877	2,877	2,877	2,877	2,877	2,877	2,877	
$DGTW_{t+1:t+756}$	0.72	-1.16	-1.97**	-1.59	-2.71*	-2.33***	-2.47*	-1.81*	-3.99***	-4.94***	-5.66***	*-54.45%*
	(0.55)	(-1.25)	(-2.29)	(-1.57)	(-1.93)	(-3.31)	(-1.87)	(-1.69)	(-4.41)	(-3.26)	(-4.68)	
#Obs	2,641	2,641	2,641	2,641	2,641	2,641	2,641	2,641	2,641	2,641	2,641	

Panel B: Regressing Abnormal Returns on REG

	(1) $DGTW_{t+1:t+21}$	(2) $DGTW_{t+1:t+63}$	(3) $DGTW_{t+1:t+126}$	(4) $DGTW_{t+1:t+252}$	(5) $DGTW_{t+1:t+504}$	(6) $DGTW_{t+1:t+756}$
REG	-2.840***	-4.235***	-4.588***	-5.573***	-6.392*	-7.209**
	(-9.16)	(-6.27)	(-4.27)	(-3.3)	(-1.93)	(-2.08)
SUE	0.104***	0.124***	0.165***	0.194***	0.328***	0.452***
	(9.29)	(5.34)	(6.62)	(4.51)	(3.96)	(4.76)
DGTW	0.107***	0.206***	0.223***	0.269***	0.287**	0.276**
	(10.09)	(9.15)	(6.19)	(4.43)	(2.27)	(2.52)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	10.05%	9.29%	8.8%	8.37%	8%	7.57%
#Days	3,012	2,975	2,940	2,855	2,694	2,540
#Obs	225,160	221,035	215,724	205,089	184,741	166,393

Table 3 – *REG* and Institutional Trading

This table reports results from daily Fama-MacBeth cross-sectional regressions of institutional trading on *REG*. In particular, column (1) of Panel A displays the result from daily cross-sectional regressions of day-t institutional investors' directional trading ($InstDirTrd$) on *REG* and other explanatory variables. Columns (2)–(5) of Panel A report the results from daily cross-sectional regressions of cumulative institutional investors' directional trading from day $t+1$ to $t+n$ ($n = 5, 10, 15,$ and 20) on *REG* and other explanatory variables. Panel B reports the total effects, repeating the regressions by replacing the dependent variable with cumulative institutional investors' directional trading from day t to $t+n$. Control variables include *LnSIZE*, *LnBM*, *RET5*, *RET21*, *MOM*, *RVOL*, and *ILLIQ*. The sample period is from January 1985 to December 2018. We report value-weighted time-series averages of the cross-sectional regression estimates based on the daily number of cross-sectional observations. An overview of all variable definitions and descriptions is provided in Internet Appendix Table IA.1. t-statistics based on Newey-West standard errors are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Contemporaneous and Predictive Effects

	$InstDirTrd_t$ (1)	$InstDirTrd_{t+1:t+5}$ (2)	$InstDirTrd_{t+1:t+10}$ (3)	$InstDirTrd_{t+1:t+15}$ (4)	$InstDirTrd_{t+1:t+20}$ (5)
REG	3.939***	9.481***	8.587***	5.154	3.405
	(8.00)	(5.70)	(6.45)	(1.32)	(0.73)
SUE	0.010	0.257***	0.498***	0.693***	0.848***
	(0.55)	(3.75)	(4.50)	(4.16)	(4.13)
DGTW	0.047***	0.171***	0.404***	0.633***	0.829***
	(4.20)	(4.07)	(5.66)	(6.00)	(6.34)
Controls	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	1.11%	0.56%	0.67%	0.92%	1.09%
#Days	1,265	1,265	1,263	1,262	1,262
#Obs	100,594	100,534	100,455	100,367	100,279

Panel B: Total Effects

	$InstDirTrd_{t:t+5}$ (1)	$InstDirTrd_{t:t+10}$ (2)	$InstDirTrd_{t:t+15}$ (3)	$InstDirTrd_{t:t+20}$ (4)
REG	13.411***	12.553***	9.094**	7.353
	(7.15)	(4.30)	(2.26)	(1.54)
SUE	0.267***	0.508***	0.702***	0.857***
	(3.54)	(4.39)	(4.12)	(4.07)
DGTW	0.218***	0.451***	0.681***	0.876***
	(4.58)	(5.82)	(6.10)	(6.38)
Controls	Yes	Yes	Yes	Yes
Adj. R-squared	0.86%	0.88%	1.08%	1.21%
#Days	1,265	1,263	1,262	1,262
#Obs	100,534	100,455	100,367	100,279

Table 4 – The Effect of *REG* on Analyst Earnings Forecast Errors

This table reports the results from daily Fama-MacBeth cross-sectional regressions of AFE in quarters $q+1$ to $q+12$ on REG and other explanatory variables (AFE, $DGTW$, and SYY) in quarter q. AFE, $DGTW$, and SYY are analyst forecast errors, earnings announcement day DGTW-adjusted abnormal returns, and firms' Stambaugh et al. (2015) score. Firm control variables include *LnSIZE*, *LnBM*, *RET5*, *RET21*, *MOM*, *RVOL*, *ILLIQ*, *DISP*, and *NUMEST*. The sample period is from January 1985 to December 2018. We report value-weighted time-series averages of the cross-sectional regression estimates based on the daily number of cross-sectional observations. An overview of all variable definitions and descriptions is provided in Internet Appendix Table IA.1. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	(1) AFE_{q+1}	(2) AFE_{q+2}	(3) AFE_{q+3}	(4) AFE_{q+4}	(5) AFE_{q+8}	(6) AFE_{q+12}
REG	2.464***	1.699***	1.397***	1.541***	1.253***	0.979***
	(11.93)	(7.23)	(5.21)	(5.87)	(4.29)	(4.10)
AFE	0.135***	0.096***	0.077***	0.068***	0.062***	0.047***
	(13.62)	(8.33)	(6.28)	(5.45)	(4.03)	(3.98)
DGTW	-0.076***	-0.048***	-0.048***	-0.043***	-0.035***	-0.015*
	(-9.19)	(-5.89)	(-3.27)	(-5.04)	(-3.53)	(-1.84)
SYY	0.016***	0.020***	0.017***	0.015***	0.018***	0.016***
	(9.74)	(8.77)	(9.01)	(8.47)	(8.00)	(7.99)
LnSIZE	-0.092***	-0.053**	-0.071***	-0.079***	-0.109***	-0.127***
	(-4.63)	(-2.50)	(-3.32)	(-3.50)	(-4.45)	(-4.46)
LnBM	0.158***	0.149***	0.101**	0.129***	0.130***	0.057*
	(4.45)	(4.08)	(2.55)	(3.08)	(3.77)	(1.65)
RET5	-0.008	0.000	-0.007	-0.005	0.008	0.001
	(-1.62)	(0.03)	(-1.23)	(-0.94)	(1.28)	(0.15)
RET21	-0.010***	-0.008***	-0.007**	-0.008**	-0.002	-0.004
	(-3.78)	(-2.94)	(-2.41)	(-2.28)	(-0.59)	(-1.35)
MOM	-0.006***	-0.005***	-0.003***	-0.001	0.002***	0.002***
	(-10.82)	(-6.67)	(-4.24)	(-1.43)	(2.79)	(2.80)
RVOL	-0.027	0.303*	-0.035	0.161	-0.420**	-0.665***
	(-0.20)	(1.94)	(-0.17)	(0.84)	(-2.22)	(-3.24)
ILLIQ	1.763**	1.702*	2.566**	3.384**	2.202	-2.052
	(2.06)	(1.81)	(2.45)	(2.02)	(0.77)	(-1.07)
DISP	28.684***	9.512	23.271***	20.502***	14.924*	40.856***
	(4.30)	(1.62)	(3.15)	(3.33)	(1.81)	(4.97)
NUMEST	-0.103**	-0.189***	-0.140***	-0.063	-0.068	-0.016
	(-2.07)	(-3.73)	(-2.95)	(-1.12)	(-1.23)	(-0.28)
Adj. R-squared	9.19%	7.62%	6.28%	5.64%	4.78%	3.61%
#Days	2,355	2,330	2,321	2,297	2,203	2,043
#Obs	172,926	168,681	165,079	162,126	150,073	134,978

Table 5 – *REG* and *SYY* Composite Mispricing Scores

This table reports results from monthly Fama-MacBeth cross-sectional regressions of firms' *SYY* scores in months $m+3$ to $m+36$ on *REG* and other explanatory variables (*AFE*, *DGTW*, and *SYY*) in month m. Firm control variables include *LnSIZE*, *LnBM*, *MRET*, *MMOM*, *MRVOL*, and *MILLIQ*. All variables except for *REG*, *AFE*, and *DGTW* are observed at the end of the month of the earnings announcement. The sample period is from January 1985 to December 2018. We report value-weighted time-series averages of the cross-sectional regression estimates based on the number of cross-sectional observations. An overview of all variable definitions and descriptions is provided in Internet Appendix Table IA.1. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	(1) SYY_{m+3}	(2) SYY_{m+6}	(3) SYY_{m+9}	(4) SYY_{m+12}	(5) SYY_{m+24}	(6) SYY_{m+36}
REG	2.304***	2.939***	2.999***	2.653***	1.097***	0.602*
	(11.07)	(11.34)	(9.97)	(8.60)	(2.93)	(1.80)
AFE	0.059***	0.030***	0.040***	0.030***	0.022**	0.024**
	(9.91)	(4.21)	(4.64)	(2.80)	(2.20)	(2.51)
DGTW	-0.087***	-0.098***	-0.084***	-0.067***	-0.017	0.005
	(-10.84)	(-8.90)	(-6.77)	(-4.87)	(-1.19)	(0.37)
SYY	0.841***	0.769***	0.662***	0.559***	0.463***	0.409***
	(86.00)	(73.43)	(64.64)	(112.68)	(84.01)	(69.60)
LnSIZE	-0.232***	-0.383***	-0.571***	-0.755***	-1.000***	-1.010***
	(-7.74)	(-9.66)	(-11.42)	(-15.20)	(-17.44)	(-15.83)
LnBM	-0.263***	-0.340***	-0.246***	0.007	0.614***	1.096***
	(-5.26)	(-4.98)	(-3.11)	(0.08)	(7.88)	(11.03)
MRET	-0.124***	-0.116***	-0.102***	-0.096***	0.036***	0.017***
	(-32.53)	(-26.42)	(-21.41)	(-17.87)	(6.66)	(3.05)
MMOM	0.008***	0.035***	0.065***	0.091***	0.091***	0.069***
	(6.70)	(24.46)	(36.47)	(42.11)	(37.33)	(29.58)
MRVOL	2.757***	3.677***	4.637***	5.673***	-4.042**	-7.279***
	(2.64)	(2.85)	(3.42)	(4.15)	(-2.34)	(-3.73)
MILLIQ	-0.496***	-0.515**	-0.902***	-1.308***	-1.245***	-0.478
	(-3.53)	(-2.55)	(-3.34)	(-3.20)	(-3.88)	(-1.24)
Adj. R-squared	76.42%	62.77%	47.56%	36.03%	27.06%	22.64%
#Months	203	202	200	197	188	182
#Obs	129,589	125,581	122,006	118,183	106,572	95,984

Table 6 – *REG* and Mispricing Scores for Individual Anomalies

This table presents the coefficients on *REG* from monthly Fama-MacBeth cross-sectional regressions of firms' cross-sectional rankings with respect to anomaly-related firm characteristics in months $m+3$ to $m+36$ on *REG* and other explanatory variables (including *AFE*, *DGTW*, and the *individual* mispricing scores) in month m. Every month, all firms are ranked into 100 bins based on each anomaly-related characteristic, such that a higher ranking is associated with a greater extent of over-valuation. Panel A reports the results for management-related anomalies, and Panel B reports the results for performance-related anomalies. Details of the anomalies and firm characteristics can be found in Internet Appendix Table IA.4. Firm control variables include *LnSIZE*, *LnBM*, *MRET*, *MMOM*, *MRVOL*, and *MILLIQ*. All variables except for *REG*, *AFE*, and *DGTW* are observed at the end of the month of the earnings announcement. The sample period is from January 1985 to December 2018. We report value-weighted time-series averages of the cross-sectional regression estimates based on the number of cross-sectional observations. An overview of all variable definitions and descriptions is provided in Internet Appendix Table IA.1. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Management

	(1) $m+3$	(2) $m+6$	(3) $m+9$	(4) $m+12$	(5) $m+24$	(6) $m+36$
CompEquIss	1.261***	1.745***	2.385***	2.674***	5.706***	7.566***
	(3.52)	(3.55)	(4.27)	(4.10)	(7.65)	(8.54)
NetStkIss	0.027	0.544	1.174**	1.645**	2.682***	3.939***
	(0.09)	(1.31)	(1.98)	(2.35)	(4.02)	(5.35)
Inv	1.231***	2.338***	3.699***	4.209***	-1.029	-2.460***
	(3.44)	(4.71)	(6.31)	(6.09)	(-1.44)	(-3.27)
NOA	0.702***	1.148***	1.525***	1.500***	0.239	0.035
	(3.63)	(4.63)	(5.15)	(4.61)	(0.61)	(0.07)
Accruals	1.524***	1.382***	1.346**	0.385	-3.375***	-2.615***
	(3.57)	(2.83)	(2.41)	(0.58)	(-4.79)	(-4.20)
Growth	0.497*	0.605	-0.101	-0.821	-4.650***	-4.105***
	(1.69)	(1.52)	(-0.21)	(-1.41)	(-6.93)	(-6.23)

Panel B: Performance

	(1) $m+3$	(2) $m+6$	(3) $m+9$	(4) $m+12$	(5) $m+24$	(6) $m+36$
Distress	1.691***	1.901***	1.855***	1.612***	2.183***	3.113***
	(3.25)	(3.72)	(3.48)	(2.78)	(3.59)	(4.79)
OScore	0.198	0.260	-0.097	-0.107	-0.180	-0.378
	(0.81)	(0.91)	(-0.26)	(-0.24)	(-0.36)	(-0.62)
GP	0.577***	1.205***	2.067***	3.186***	3.339***	2.224***
	(3.26)	(5.22)	(7.52)	(10.84)	(7.40)	(4.80)
ROA	11.995***	9.509***	7.151***	5.395***	3.664***	1.616***
	(19.25)	(16.80)	(12.25)	(9.78)	(6.70)	(2.74)
MOM	4.471***	6.845***	5.542***	3.532***	3.061***	1.862**
	(8.17)	(10.12)	(7.93)	(4.73)	(4.32)	(2.46)

Table 7 – REG and Anomaly Returns

This table reports the cumulative monthly $DGTW$ abnormal returns (expressed in percent) of portfolios formed based on the quintile ranking of SYY mispricing scores at the end of month $m-1$ and the sign of REG in month m. Portfolio returns are presented for different horizons from month m (including the earnings announcement month) to $m+n$ ($n = 1, 3, 6, 12, 24, 36$) and from month $m+1$ (excluding the earnings announcement month) to $m+n$ ($n = 3, 6, 12, 24, 36$). In Panel A, portfolio "Q5" ("Q1") holds stocks with SYY ranking in the top (bottom) quintile that captures overvaluation (undervaluation). Portfolio Q5-Q1 is the difference between Q5 and Q1, predicted to yield a negative return according to the SYY anomaly correction path. Panel A also reports abnormal returns of four portfolios formed on SYY being in the top (bottom) quintile and the REG realization being positive (negative). In Panel B, the "REG Against" portfolio is formed based on the REG realization being against the SYY correction path, that is, it takes a long position in stocks with SYY scores being in the top quintile in month $m-1$ and a positive realization of REG in month m ($REG > 0$), and a short position in stocks with SYY scores being in the bottom quintile in month $m-1$ and a negative realization of REG in month m ($REG < 0$). The "REG With" portfolio is formed based on the REG realization being with the SYY correction path, that is, it takes a long position in stocks with SYY scores being in the top quintile in month $m-1$ and a negative realization of REG in month m ($REG < 0$), and a short position in stocks with SYY scores being in the bottom quintile in month $m-1$ and a positive realization of REG in month m ($REG > 0$). The sample period is from January 1985 to December 2018. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Portfolios Based on SYY *and* REG

	$MDGTW_m$	$MDGTW_{m:m+1}$	$MDGTW_{m:m+3}$	$MDGTW_{m:m+6}$	$MDGTW_{m:m+12}$	$MDGTW_{m:m+24}$	$MDGTW_{m:m+36}$
<u>SYY Portfolios</u>							
SYY Q5 (Overvalued)	0.09	-0.08	-0.64***	-1.78***	-2.71***	-2.43***	-1.56
	(0.76)	(-0.53)	(-2.62)	(-5.59)	(-5.88)	(-3.51)	(-1.55)
SYY Q1 (Undervalued)	0.41***	0.66***	0.90***	1.22***	1.40***	2.43***	3.09***
	(4.86)	(6.31)	(5.89)	(5.45)	(4.00)	(4.77)	(4.41)
SYY Q5-Q1	-0.32**	-0.74***	-1.54***	-3.00***	-4.10***	-4.86***	-4.66***
	(-2.22)	(-4.14)	(-5.52)	(-7.75)	(-6.99)	(-5.43)	(-3.56)
<u>SYY and REG Portfolios</u>							
SYY Q5 & $REG > 0$	1.75***	1.62***	0.60*	-0.85	-1.95***	-2.30**	-2.08
	(9.68)	(7.22)	(1.67)	(-1.62)	(-3.01)	(-2.09)	(-1.53)
SYY Q5 & $REG < 0$	-1.94***	-1.94***	-2.64***	-3.34***	-3.99***	-3.54***	-2.21
	(-10.00)	(-8.07)	(-8.33)	(-6.54)	(-5.20)	(-3.15)	(-1.50)
SYY Q1 & $REG > 0$	1.82***	2.09***	2.25***	2.45***	2.63***	3.30***	4.39***
	(18.43)	(16.49)	(12.75)	(9.02)	(5.17)	(3.99)	(3.88)
SYY Q1 & $REG < 0$	-0.95***	-0.66***	-0.37*	-0.09	0.39	1.57*	2.68**
	(-7.60)	(-4.54)	(-1.67)	(-0.25)	(0.75)	(1.75)	(2.17)

Panel B: Portfolios Based on REG *Being Against or With the* SYY *Correction Path*

	$MDGTW_m$	$MDGTW_{m:m+1}$	$MDGTW_{m:m+3}$	$MDGTW_{m:m+6}$	$MDGTW_{m:m+12}$	$MDGTW_{m:m+24}$	$MDGTW_{m:m+36}$
REG Against	2.66***	2.26***	0.99**	-0.81	-2.47***	-3.87***	-4.69**
	(11.61)	(7.72)	(2.13)	(-1.17)	(-2.68)	(-2.62)	(-2.57)
REG With	-3.77***	-4.04***	-4.91***	-5.72***	-6.56***	-6.76***	-6.55***
	(-15.99)	(-13.69)	(-12.18)	(-9.24)	(-6.44)	(-4.75)	(-2.96)
REG Against - REG With	6.43***	6.30***	5.90***	4.91***	4.09***	2.89	1.86
	(19.56)	(15.16)	(9.59)	(5.29)	(2.98)	(1.41)	(0.65)

	$MDGTW_{m+1}$	$MDGTW_{m+1:m+3}$	$MDGTW_{m+1:m+6}$	$MDGTW_{m+1:m+12}$	$MDGTW_{m+1:m+24}$	$MDGTW_{m+1:m+36}$
REG Against	-0.42**	-1.64***	-3.37***	-5.07***	-6.34***	-6.93***
	(-2.55)	(-4.75)	(-6.09)	(-6.76)	(-4.58)	(-3.48)
REG With	-0.28	-1.11***	-1.99***	-2.85***	-3.04**	-2.83
	(-1.47)	(-3.36)	(-3.73)	(-3.08)	(-2.43)	(-1.41)
REG Against - REG With	-0.14	-0.53	-1.38*	-2.22*	-3.30*	-4.10
	(-0.56)	(-1.11)	(-1.80)	(-1.86)	(-1.77)	(-1.45)

Table 8 – The Effect of *REG* on *AFE*: Analyst Promptness

This table reports the results from daily Fama-MacBeth cross-sectional regressions of future average analyst forecast errors on *REG* for analysts with different degrees of promptness. Analyst forecasts for quarter $q+1$ earnings are categorized into four groups dependent on when they are issued after the firm's earnings announcement in quarter q (day t): $Prompt = 1$ if the earnings forecast is issued during the window [t+1:t+10], $Prompt = 2$ if the earnings forecast is issued during [t+11:t+30], $Prompt = 3$ if the earnings forecast is issued during [t+31:t+60], and $Prompt = 4$ if the earnings forecast is issued more than 60 days after day t. For each group, we compute the average analyst forecast error, labeled as $AFE^{Prompt=1}$, $AFE^{Prompt=2}$, $AFE^{Prompt=3}$, and $AFE^{Prompt=4}$, respectively, and run four separate regressions with each of them as a dependent variable. We include (aggregate) *AFE*, *DGTW*, *SYY*, and the full set of control variables. In addition, we control for the number of days between the release of individual analysts' forecasts and the release of quarter $q+1$ earnings. The sample period is from January 1985 to December 2018. We report value-weighted time-series averages of the cross-sectional regression estimates based on the daily number of cross-sectional observations. An overview of all variable definitions and descriptions is provided in Internet Appendix Table IA.1. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	(1) $AFE_{q+1}^{Prompt=1}$	(2) $AFE_{q+1}^{Prompt=2}$	(3) $AFE_{q+1}^{Prompt=3}$	(4) $AFE_{q+1}^{Prompt=4}$
REG	4.695***	3.998**	2.175**	1.232*
	(5.13)	(2.17)	(2.14)	(1.91)
AFE	0.052	0.115	0.102*	0.134***
	(1.21)	(1.12)	(1.90)	(5.15)
DGTW	-0.148***	-0.139**	-0.104***	-0.026
	(-4.56)	(-2.32)	(-3.05)	(-1.23)
SYY	0.030***	0.017	0.021**	0.017***
	(3.60)	(1.43)	(2.34)	(3.26)
Controls	Yes	Yes	Yes	Yes
Adj. R-squared	10.29%	11.23%	10.6%	9.3%
#Days	1,820	1,543	1,764	1,652
#Obs	127,802	86,851	101,395	108,566

Table 9 – The Effect of REG on AFE Conditioning on Analyst Characteristics

This table reports results from panel regressions of individual analyst forecast errors (AFE) in quarters $q+1$ to $q+4$ on quarter-q REG, the interaction of REG with analyst characteristics, and other control variables. We consider two analyst characteristics: the degree of analyst industry concentration and analyst accuracy. To capture industry concentration, we construct $Rank(NumInd)$ as the decile ranking based on the number of industries covered by an analyst in a given quarter. To capture accuracy, we use the Clement (1999) $PMAFE$ (Proportionate Mean Absolute Forecast Error) measure, and construct $Rank(PMAFE)$ as the decile ranking of an analyst's stock-level $PMAFE$ over the past year. We include AFE, $DGTW$, SYY, and the full set of control variables. In addition, we control for the number of days between the analyst's earnings forecast and the earnings announcement. The sample period is from January 1985 to December 2018. An overview of all variable definitions and descriptions is provided in Internet Appendix Table IA.1. All the regressions include analyst and quarter fixed effects, and standard errors are clustered on analyst and quarter. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	(1) AFE_{q+1}	(2) AFE_{q+2}	(3) AFE_{q+3}	(4) AFE_{q+4}
	Industry Concentration: Generalist vs. Specialist			
REG	1.809***	1.828***	1.648***	1.359***
	(5.43)	(3.72)	(3.88)	(5.19)
$Rank(NumInd)$	-0.004	0.013	-0.002	-0.001
	(-0.68)	(1.40)	(-0.33)	(-0.09)
$REG \times Rank(NumInd)$	0.101***	0.032	0.040	0.054
	(3.51)	(1.17)	(1.26)	(1.64)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Analyst, Quarter	Analyst, Quarter	Analyst, Quarter	Analyst, Quarter
Adj. R-squared	11.93%	3.88%	4.36%	3.28%
#Obs	622,831	572,326	527,047	490,863
	Analyst Accuracy: Accurate vs. Inaccurate			
REG	1.781***	1.134***	1.298***	1.580***
	(3.19)	(2.87)	(6.37)	(6.23)
$Rank(PMAFE)$	-0.020***	-0.015***	-0.015***	-0.009**
	(-7.27)	(-4.94)	(-4.02)	(-2.50)
$REG \times Rank(PMAFE)$	0.052***	0.034**	0.035**	0.033**
	(3.67)	(2.22)	(2.41)	(2.01)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Analyst, Quarter	Analyst, Quarter	Analyst, Quarter	Analyst, Quarter
Adj. R-squared	4.64%	4.79%	3.63%	3.53%
#Obs	405,404	376,503	350,896	329,871

Table 10 – The Effect of *REG* on *SYY* Conditioning on the Firm Information Environment

This table reports the coefficient on *REG* from monthly Fama-MacBeth cross-sectional regressions of firms' *SYY* scores in months m+3 to m+36 on *REG* and other explanatory variables in month m. The difference between the coefficients on *REG* in different subsamples and the corresponding t-statistics are also reported. We consider cross-sectional subsamples based on two variables: the availability of earnings guidance and the earnings volatility. All dependent variables except for *REG*, *AFE*, and *DGTW*, are observed at the end of the month of earnings announcement day t. Firm control variables include *LnSIZE*, *LnBM*, *MRET*, *MMOM*, *MRVOL*, and *MILLIQ*. The sample period is from January 1985 to December 2018. We report value-weighted time-series averages of the cross-sectional regression estimates based on the daily number of cross-sectional observations. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	(1) SYY_{m+3}	(2) SYY_{m+6}	(3) SYY_{m+9}	(4) SYY_{m+12}	(5) SYY_{m+24}	(6) SYY_{m+36}
			Earnings Guidance			
Without	2.199***	2.867***	2.994***	2.683***	1.083**	0.871**
	(9.17)	(9.31)	(8.7)	(7.24)	(2.56)	(2.1)
With	1.201**	1.472**	1.193	0.651	0.763	1.264
	(2.28)	(2.23)	(1.50)	(0.84)	(0.83)	(1.62)
Without - With	0.998*	1.395*	1.801**	2.032**	0.320	-0.393
	(1.72)	(1.92)	(2.08)	(2.37)	(0.32)	(-0.44)
			Earnings Volatility			
Above Median	2.925***	3.201***	3.625***	3.459***	1.239**	0.957**
	(9.89)	(9.28)	(9.27)	(8.59)	(2.50)	(2.17)
Below Median	1.487***	2.244***	1.923***	1.865***	1.262**	0.662
	(5.63)	(6.39)	(4.60)	(3.96)	(2.42)	(1.29)
Above - Below	1.438***	0.957**	1.702***	1.594***	-0.023	0.295
	(3.63)	(1.94)	(2.97)	(2.57)	(-0.03)	(0.44)

Table 11 – *REG* and Analysts' Confirmation Bias

This table reports results from daily Fama-MacBeth cross-sectional regressions detailed in Eq. (IA.3). The dependent variable is a dummy that equals one if the *AFE* of a firm in quarter q is of the same sign as the firm's *AFE* n quarters ahead (n = 1, 2, 3, 4, 8, and 12). D(AFE_q & REG_q Same Sign) is a dummy that equals one if a firm's *AFE* in quarter q is of the same sign as its *REG* in the same quarter. D(AFE_q & AFE_{q-1} Same Sign) is a dummy variable that equals one when the *AFE* of a firm in quarter q and quarter $q-1$ are of the same sign. We include analyst forecast errors, earnings announcement day DGTW-adjusted abnormal returns, and firm mispricing scores in quarter q as controls. Firm control variables include *LnSIZE*, *LnBM*, *RET5*, *RET21*, *MOM*, *RVOL*, *ILLIQ*, *DISP*, and *NUMEST*. The sample period is from January 1985 to December 2018. We report value-weighted time-series averages of the cross-sectional regression estimates based on the daily number of cross-sectional observations. An overview of all variable definitions and descriptions is provided in Internet Appendix Table IA.1. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	D(AFE_q & AFE_{q+n} Same Sign)					
	$n=1$	$n=2$	$n=3$	$n=4$	$n=8$	$n=12$
	(1)	(2)	(3)	(4)	(5)	(6)
D(AFE_q & REG_q Same Sign)	0.127***	0.111***	0.104***	0.107***	0.102***	0.098***
	(37.75)	(34.12)	(32.66)	(31.28)	(28.71)	(25.74)
D(AFE_q & AFE_{q-1} Same Sign)	0.208***	0.198***	0.205***	0.176***	0.155***	0.150***
	(64.78)	(58.77)	(60.50)	(50.81)	(42.20)	(38.72)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	10.63%	9.98%	9.67%	8.62%	8.19%	8.38%
#Days	2,197	2,162	2,144	2,119	2,026	1,879
#Obs	159,697	155,970	152,986	150,025	139,139	125,029

Table 12 – The Effect of *REG* on *SYY* Scores: Amplification

This table extends the analysis conducted in Table 5 and reports results from monthly Fama-MacBeth cross-sectional regressions of firms' *SYY* scores in months $m+3$ to $m+36$ on *REG* and the interaction of *REG* with an amplification dummy D(Amplification), which equals one when *REG* and *AFE* are of the same sign in a given quarter, and zero otherwise. Other explanatory variables (*AFE*, *DGTW*, and *SYY*) in month m are also included. Firm control variables include *LnSIZE*, *LnBM*, *MRET*, *MMOM*, *MRVOL*, and *MILLIQ*. All variables except for *REG*, *AFE*, and *DGTW* are observed at the end of the month of the earnings announcement. The sample period is from January 1985 to December 2018. We report value-weighted time-series averages of the cross-sectional regression estimates based on the number of cross-sectional observations. An overview of all variable definitions and descriptions is provided in Internet Appendix Table IA.1. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	(1) SYY_{m+3}	(2) SYY_{m+6}	(3) SYY_{m+9}	(4) SYY_{m+12}	(5) SYY_{m+24}	(6) SYY_{m+36}
REG × D(Amplification)	1.656***	2.294***	2.685***	2.851***	2.289***	1.339*
	(5.64)	(6.32)	(5.80)	(5.43)	(3.84)	(1.90)
REG	0.857**	0.992**	0.738	0.314	-0.786	-0.316
	(2.58)	(2.51)	(1.54)	(0.56)	(-1.23)	(-0.47)
D(Amplification)	0.020	0.106**	0.135**	0.178**	0.139*	0.352***
	(0.51)	(1.99)	(1.98)	(2.52)	(1.71)	(4.52)
AFE	0.057***	0.027***	0.036***	0.025**	0.020*	0.021**
	(9.60)	(3.78)	(4.22)	(2.38)	(1.96)	(2.21)
DGTW	-0.075***	-0.082***	-0.067***	-0.048***	-0.004	0.013
	(-9.27)	(-7.44)	(-5.37)	(-3.43)	(-0.25)	(0.95)
SYY	0.841***	0.768***	0.661***	0.558***	0.462***	0.409***
	(85.82)	(73.22)	(64.54)	(112.79)	(84.02)	(69.60)
LnSIZE	-0.218***	-0.363***	-0.550***	-0.734***	-0.983***	-0.999***
	(-7.42)	(-9.23)	(-11.04)	(-14.87)	(-16.93)	(-15.54)
LnBM	-0.278***	-0.362***	-0.273***	-0.021	0.588***	1.074***
	(-5.57)	(-5.3)	(-3.47)	(-0.26)	(7.60)	(10.80)
MRET	-12.35***	-11.552***	-10.198***	-9.553***	3.614***	1.784***
	(-32.36)	(-26.17)	(-21.26)	(-17.78)	(6.77)	(3.14)
MMOM	0.783***	3.466***	6.463***	9.038***	9.065***	6.861***
	(6.79)	(24.54)	(36.45)	(42.03)	(37.32)	(29.62)
MRVOL	2.765***	3.762***	4.743***	5.889***	-3.935**	-7.077***
	(2.66)	(2.93)	(3.5)	(4.3)	(-2.29)	(-3.64)
MILLIQ	-0.455***	-0.472**	-0.875***	-1.331***	-1.243***	-0.474
	(-3.36)	(-2.31)	(-3.27)	(-3.29)	(-3.85)	(-1.21)
Adj. R-squared	76.44%	62.81%	47.62%	36.08%	27.09%	22.71%
#Months	201	199	198	193	186	181
#Obs	129,589	125,581	122,006	118,183	106,572	95,984

A Appendix

A Simple Model of REG*, Biased Beliefs, and Slow Mispricing Correction*

We present a simple model that explains the predictive power of *REG* for analyst forecast errors and management actions as well as the slow correction of mispricing that we observe in the data. The model explicitly accounts for the dynamic expectation formation of investors on the one side and analysts and managers on the other side, and demonstrates how biases can propagate between the two groups of agents. Our setup thus extends the literature on belief updating, which often implicitly or explicitly equalizes the expectations of different agents.[20]

Setup We consider a cross-section of firms that are indexed by i. The earnings per share $x_{i,t}$ of firm i evolve as

$$x_{i,t} = \rho_x x_{i,t-1} + f_{i,t} + \varepsilon_{i,t} \tag{8}$$

with mean-reversion parameter ρ_x, earnings growth trend $f_{i,t}$, and temporary earnings shocks $\varepsilon_{i,t} \sim N(0, \sigma_\varepsilon^2)$. The dynamics of the earnings growth trend are given by

$$f_{i,t} = \rho_f f_{i,t-1} + \eta_{i,t} \tag{9}$$

with mean-reversion parameter ρ_f and growth trend shocks $\eta_{i,t} \sim N(0, \sigma_\eta^2)$.

[20] Notable exceptions are Malmendier and Shanthikumar (2007), who examine to what extent traders take into account the analysts' affiliation bias when interpreting their recommendations, and Ke et al. (2023), who find that the relaxation of short-sale constraints (and increased price efficiency) positively influences analyst forecast accuracy. Engelberg et al. (2020) also conceptually distinguish both types of agents when highlighting the implications of their empirical results.

Investors, Analysts, and Managers There are two types of agents in the model, on the one side investors, and on the other side analysts and managers.[21] The agents form expectations about the unobservable fundamental $f_{i,t}$ based on observations of three pieces of information: the firm's earnings per share $x_{i,t}$, a private signal, as well as an inferred private signal of the other type of agent. In particular, analysts and managers infer the investors' private signal from the market response on the earnings announcement day, while investors infer the analysts' and managers' private signal from the previously published analyst forecasts and implemented management actions.

Formally, investors observe a private signal $s_{i,t} = f_{i,t} + b_{i,t} + \chi_{i,t}$, with noise term $\chi_{i,t} \sim N(0, \sigma_\chi^2)$, and we explicitly model that the signal is confounded by a bias $b_{i,t}$ that the investors are not aware of. The bias is the main source of *REG* in the model, as it produces a departure of investor expectations from fundamentals. We assume that $b_{i,t}$ is persistent and follows the process

$$b_{i,t} = \rho_b b_{i,t-1} + \nu_{i,t} \tag{10}$$

with mean-reversion parameter ρ_b and shocks $\nu_{i,t} \sim N(0, \sigma_b^2)$. Analysts and managers observe a private signal $c_{i,t} = f_{i,t} + \phi_{i,t}$, with $\phi_{i,t} \sim N(0, \sigma_\phi^2)$.

Investors (denoted by "I") infer the private signal of the analysts and managers from time $t-1$ by observing published analyst forecasts and implemented management actions, respectively, assuming that $\tilde{c}_{i,t-1} = f_{i,t-1} + \phi_{i,t-1}$ holds for the inferred signal $\tilde{c}_{i,t-1}$. They

[21]For simplicity, we do not additionally model the beliefs of analysts and managers separately. Gennaioli et al. (2016) find that the expectations of CFOs and analysts are highly correlated.

update their expectations about $f_{i,t}$ according to

$$\tilde{f}^I_{i,t} = \rho_f \tilde{f}^I_{i,t-1} + K_1(x_{i,t} - \rho_x x_{i,t-1} - \rho_f \tilde{f}^I_{i,t-1}) + K_2(s_{i,t} - \rho_f \tilde{f}^I_{i,t-1}) + K_3(\tilde{c}^I_{i,t-1} - \tilde{f}^I_{i,t-1}), \quad (11)$$

following the standard Bayesian updating rule.[22]

Analysts and managers (denoted by "A") infer the time-t private signal of the investors by observing market prices, as discussed below. We now distinguish two different cases that we analyze within our framework. In the first case, analysts/managers are not aware of the investors' bias, and they assume that their inferred signal $\tilde{s}^A_{i,t}$ is an unbiased signal of the fundamental, $\tilde{s}^A_{i,t} = f_{i,t} + \chi_{i,t}$. In this case, their expectations about $f_{i,t}$ follow the process

$$\tilde{f}^A_{i,t} = \rho_f \tilde{f}^A_{i,t-1} + K_1(x_{i,t} - \rho_x x_{i,t-1} - \rho_f \tilde{f}^A_{i,t-1}) + K_2(\tilde{s}^A_{i,t} - \rho_f \tilde{f}^A_{i,t-1}) + K_3(c_{i,t} - \rho_f \tilde{f}^A_{i,t-1}). \quad (12)$$

In the second case, analysts/managers know of the investors bias $b_{i,t}$, and they assume (correctly) $\tilde{s}^A_{i,t} = f_{i,t} + b_{i,t} + \chi_{i,t}$ and thus correct for the bias. Consequently, their expectations about $f_{i,t}$ then follow

$$\tilde{f}^A_{i,t} = \rho_f \tilde{f}^A_{i,t-1} + K_1(x_{i,t} - \rho_x x_{i,t-1} - \rho_f \tilde{f}^A_{i,t-1}) + K_2(\tilde{s}^A_{i,t} - b_{i,t} - \rho_f \tilde{f}^A_{i,t-1}) + K_3(c_{i,t} - \rho_f \tilde{f}^A_{i,t-1}). \quad (13)$$

Stock Prices In the model, stock prices are determined by the investors' expectation of future cash flows, which are driven by current earnings $x_{i,t}$ and the expected earnings growth $\tilde{f}^I_{i,t}$ from the investors' perspective. Assuming a constant discount factor β and the dynamics

[22] See Liptser and Shiryaev (2001). $K = (K_1, K_2, K_3)$ is the vector of Kalman gains, which weights the different signals according to their precision.

of the earnings level and growth components given by (8) and (9), stock prices are given by

$$P_{i,t} = \sum_{n=0}^{\infty}(1+\beta)^{-n}\mathbb{E}^I[x_{i,t+n}] = \frac{(1+\beta)(\rho_f \tilde{f}^I_{i,t} + (1+\beta-\rho_f)x_{i,t})}{(1+\beta-\rho_f)(1+\beta-\rho_x)}. \tag{14}$$

Stock prices thus follow investors' earnings growth expectations linearly. Moreover, the formula confirms that analysts and managers are able to back out $\tilde{f}^I_{i,t}$ by observing stock prices $P_{i,t}$ and current earnings $x_{i,t}$, based on which they can infer the investors' signal $s_{i,t}$ by evaluating equation (11).

***REG*, Expectation Formation, and Mispricing Correction** We demonstrate the dynamic expectation formation of investors as well as analysts and managers within the model and show how *REG* induces biased analyst and management expectations and ultimately results in a slow correction of mispricing. In particular, we simulate the dynamics of expectations and stock prices over 12 quarters, as in the data, for a cross-section of 100,000 observations. Figure A.1 shows the dynamics of investors' and analysts'/managers' earnings growth expectations as well as stock prices, averaged over the cross-section, conditional on a large positive investor bias in $t = 1$ as reflected by *REG*.

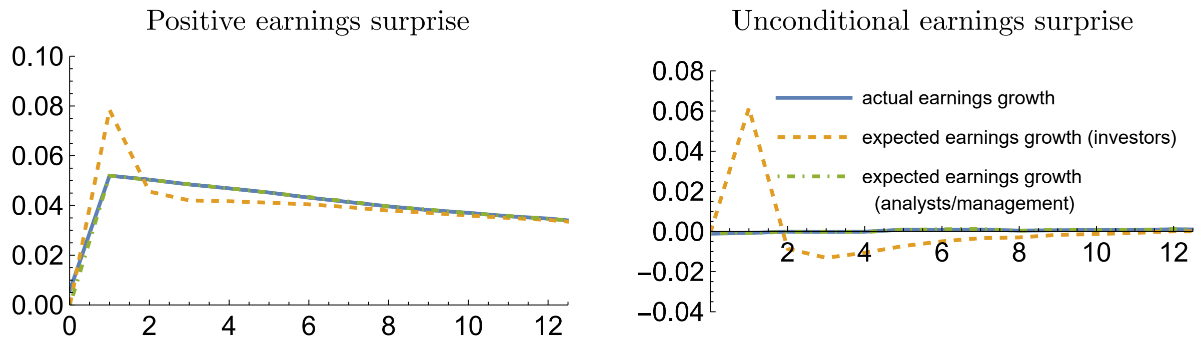
[Figure A.1]

Panel (a) depicts expectations of earnings growth for the case in which analysts and managers understand and correct for the investors' bias, $b_{i,t}$. In this case, investors' upward-biased earnings growth expectations are reflected by *REG* in $t = 1$, but do not spill over to the analysts'/managers' expectations, which align with the actual earnings growth. In fact, the analysts and managers help correct the bias of the investors in the next time period ($t = 2$), who observe and learn from analyst forecasts and management actions, such that investor expectations quickly revert back to normal levels. This correction takes place even though the investors' bias is persistent and their private signal remains elevated, since the (unbiased) analyst forecasts and management actions appear as a very negative signal from the investors' perspective and thus counteract this upward bias. The plot on the left-hand side illustrates these dynamics conditional on the fundamental earnings surprise being positive, while the right-hand side shows the unconditional case in which average earnings surprises are zero.

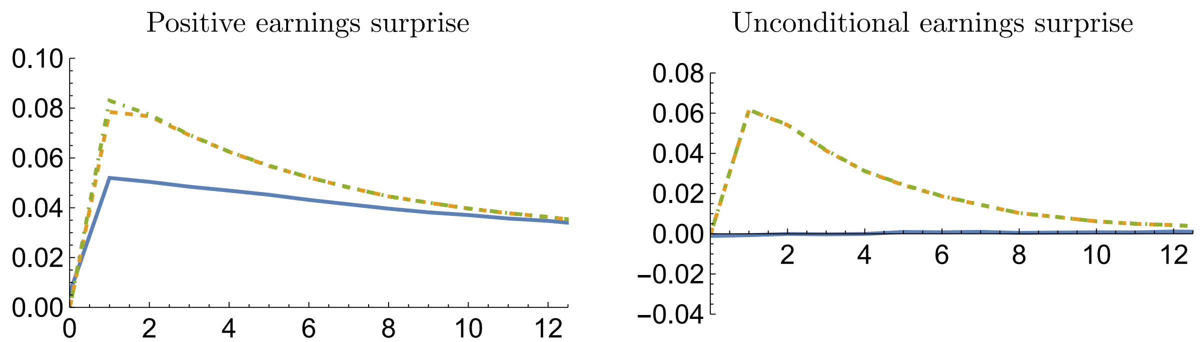
Contrasting with these dynamics, Panel (b) illustrates the case where analysts and managers are not aware of the investors' bias. As a result, an overly positive market reaction to earnings news due to biased investor beliefs spills over to the analyst and management expectations, which rise to about the same level as the investors'. When investors observe the updated analyst forecasts and implemented management actions to update their beliefs in the next period, they do not observe any correction, and they see their elevated expectations being confirmed by the analysts/managers. Consequently, the correction of both agents' upward-biased beliefs, which takes place as agents are in each period negatively surprised by the actual earnings data, is slowed down by the reconfirmation of biases through the other agent.

Panel (c) shows how the formation of expectations translates to stock price dynamics. In the case where analysts and managers understand and correct the investors' bias, the initial price increase corresponding to REG reverts to the largest extent very quickly, leading to a fast correction of the initial overreaction. On the contrary, the correction is very slow in the case where analyst expectations and management actions are affected by the initial market (mis)reaction to the earnings news. As in the data, it takes around 12 quarters until the prices in this bias spillover case reach approximately the level of the bias correction case, and the gap is substantial in the first quarters after the event date. In sum, these results show how the dynamics of investor beliefs, analyst and management expectations, and stock prices observed in the data can be jointly attributed to an initial bias in investor expectations captured by *REG*.

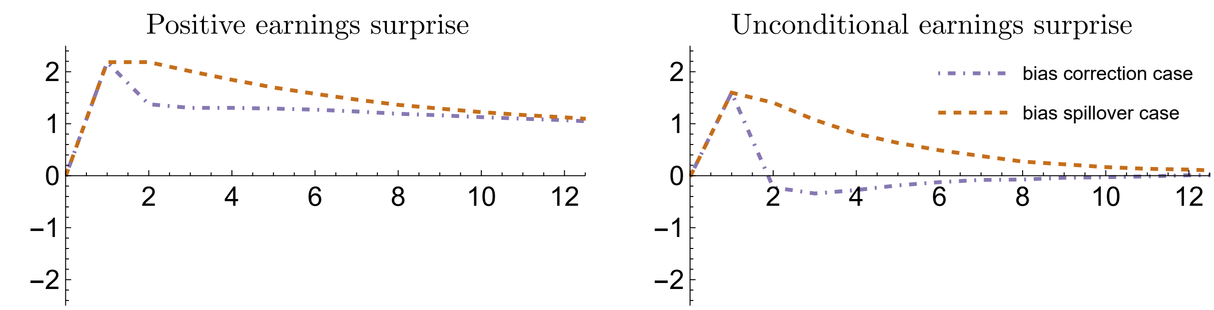
Altogether, the presented simple structural model corroborates the main mechanisms suggested by our empirical analysis. If investors' reaction to earnings news is biased and analysts and managers are not able to disentangle this bias from information, then the bias translates to analyst errors and management actions. The jointly upward-biased investor and analyst/management beliefs then result in a slow correction of stock prices, as the disappointment from fundamental earnings realizations is counteracted by the confirmatory effect of both agents' elevated expectations.



(a) Earnings growth expectations (bias correction case)



(b) Earnings growth expectations (bias spillover case)



(c) Stock prices (bias correction and spillover cases)

Fig. A.1 – Structural Model: Dynamic Expectation Formation and Stock Prices

The figures depict the average dynamics of actual earnings growth, investor and analyst/management expectations, and stock prices in response to a large positive REG at $t = 1$. We simulate a cross-section of 100,000 firm-earnings-announcement observations based on our model and plot cross-sectional averages of $f_{i,t}$, $\tilde{f}^I_{i,t}$, $\tilde{f}^A_{i,t}$, and $P_{i,t}$ over time, for positive earnings surprises in $t = 1$ (figures on the left) and unconditionally (figures on the right). Panel (a) shows the case where analysts and managers are aware of and account for the investors' bias $b_{i,t}$ (bias correction case), and Panel (b) considers the case where they are not aware of the bias and interpret it as part of the signal (bias spillover case). In Panels (a) and (b), the blue solid line shows the actual earnings growth, the yellow dashed line the earnings growth as expected by the investors, and the green dot-dashed line the earnings growth as expected by analysts and managers. In Panel (c), the dashed red line stands for stock prices in the bias spillover case and the dot-dashed purple line stands for the bias correction case. The model parameters are calibrated as $\rho_x = 0.56$, $\rho_f = 0.96$, $\sigma_\varepsilon = 0.08$, and $\sigma_\eta = 0.14$ in line with Bordalo et al. (2019), as well as $\beta = 0.04$, $\sigma_\chi = 0.09$, $\sigma_\phi = 0.18$, $\rho_b = 0.75$, and $\sigma_b = 0.09$. We consider a two-standard-deviation shock to $b_{i,t}$ to produce a large positive REG in $t = 1$ and set the subsequent shocks to $b_{i,t}$ to zero.

Internet Appendix

IA.1 Variable Definitions and Timeline

Table IA.1 reports the definitions of variables used throughout our paper.

Figure IA.1 illustrates the timeline of analyst forecast errors (AFE), the earnings announcement, and the observed return-earnings gap (REG) over two consecutive quarters.

IA.2 Post-Earnings-Announcement Drift Based on Earnings Surprises and Earnings Returns

Table IA.2 reports return spreads of single-sorted portfolios based on earnings surprises (SUE) and characteristic-adjusted earnings-day returns ($DGTW$), compared to portfolios formed based on REG.

IA.3 Analyst Forecast Errors: Monthly and Quarterly Pooling

Table IA.3 repeats the analysis conducted in Table 4, where the daily earnings announcement observations are pooled at the monthly or quarterly level in the first stage of the Fama-MacBeth cross-sectional regressions.

IA.4 SYY *Anomaly Characteristics*

Table IA.4 reports the list of Stambaugh et al.'s (2012; 2015; 2017) "management" and "performance" anomaly characteristics together with the direction of return predictability. The first eight characteristics have a negative sign, which means that higher raw values predict negative returns, while the last three have a positive sign. The ranking procedure takes this into account and ranks the last three variables in descending order. Thus, a higher ranking means lower raw values, which corresponds to lower subsequent returns.

Table IA.5 extends the analysis reported in Table 6 (on the predictive relation of REG to SYY's anomaly characteristics) and uses *raw* instead of ranked characteristics values. For example, higher REG predicts higher raw values of investment and stock issuances. At the same time, it predicts lower values of ROA and gross profitability.

IA.5 Robustness Checks of Main Results

In this section, we describe various robustness tests which demonstrate that our results do not critically hinge on particular details of the measure construction approaches, the sample selection, or the research design.

In Table IA.6, we investigate four different variants of constructing REG based on the relative rankings of (i) raw returns ($RET_{i,t}$) and unadjusted earnings surprises ($SUE_{i,t}$) in 1,000 bins, (ii) medium-horizon abnormal returns ($DGTW_{i,t:t+4}$) and adjusted earnings surprises ($AdjSUE_{i,t}$) in 1,000 bins, (iii) long-horizon abnormal returns ($DGTW_{i,t:t+20}$) and adjusted earnings surprises ($AdjSUE_{i,t}$) in 1,000 bins, and (iv) one-day abnormal returns ($DGTW_{i,t}$) and adjusted earnings surprises ($AdjSUE_{i,t}$) in 100 bins. It turns out that all REG variants yield similar results on the predictive relation to AFE and SYY scores, regardless of the different construction approaches.

Further robustness of our results is provided in Tables IA.7 and Table IA.8, where we consider subsamples for different time periods within our sample as well as panel regressions instead of the Fama-MacBeth approach.

In Tables IA.9 and IA.10, we ease concerns about a potential multicollinearity between REG, AFE, and $DGTW$ when all three variables are included in a regression. We repeat our main regressions from Tables 4 and 5 without including AFE and $DGTW$ and obtain very similar results. We also report results for AFE and $DGTW$ excluding REG and find that their coefficients do not change significantly compared to our baseline regressions. Both sets of results confirm that REG, AFE, and $DGTW$ capture separate effects.

Finally, in Table IA.11 we re-assess the impact of REG on subsequent AFE and SYY on a broader sample that includes firms with all possible fiscal year ends. Specifically, we repeat the regressions from Tables 4 and 5 on this larger sample and find that our results remain intact, implying that the documented effects are not particular to firms with fiscal year ends in December.

IA.6 Price Targets and Analyst Recommendations

Besides using analyst earnings forecasts to infer analyst expectations, we also consider analyst price targets and analyst recommendation changes. We find that the results based on these alternative analyst outputs support our main findings.

IA.6.1 Analyst Price Target Return Forecast Errors

We explore the relation between REG and analysts' price targets. We obtain 12-month price target estimates from I/B/E/S and focus on price targets that were issued by analysts over the subsequent 60 trading days following an earnings announcement. We estimate the analyst 12-month return forecast by scaling the future price target by the current stock price and subtracting one from the ratio. Then, we compute the actual 12-month return using the actually realized future price and the current price. Finally, we calculate the average return forecast error (*RetForeErr*) as the average of the difference between the forecast return minus the realized return across all analysts.

We use Fama-MacBeth regressions of the analyst implied return forecast error on *REG*. Our regression takes the following form:

$$\begin{aligned} RetForeErr_{i,t+1:t+60} =& \gamma_{0,t} + \gamma_{reg,t} REG_{i,t} + \gamma_{afe,t} AFE_{i,t} + \\ & \gamma_{dgtw,t} DGTW_{i,t} + \sum_{k=1}^{K} \gamma_{k,t} CONTROLS_{k,i,t} + \epsilon_{i,t}, \end{aligned} \tag{IA.1}$$

where $RetForeErr_{i,t+1:t+60}$ is the average analyst return forecast error of stock i over the subsequent 60 days following each earnings announcement. $REG_{i,t}$, $AFE_{i,t}$, $DGTW_{i,t}$ are the return-earnings gap, analyst earnings forecast error, and DGTW-adjusted daily abnormal return of stock i as of the earnings announcement day t in quarter q. We include the standard set of controls for firm characteristics. We compute time-series value-weighted averages of coefficients based on the daily number of cross-sectional observations as done in previous sections.

The regression results are reported in Table IA.12. Column (1) shows the result based on all observations: the coefficient on *REG* is 2.841 with a t-statistics of 2.11, implying that analysts are also too optimistic (pessimistic) in terms of their future price target estimations given high (low) values of *REG*. Columns (2) and (3) repeat the analysis, where we require at least two or three analysts to issue future price targets for the same stock. Overall, consistent with our earnings forecast findings, we find a positive relation between *REG* and future analyst errors.

IA.6.2 Analyst Recommendation Changes

Next, we examine how analysts update their recommendations after observing investors' (mis)reaction on earnings announcement days. We construct analyst recommendation changes

(*RecChng*) as the average numerical change of recommendations issued by analysts during the following few weeks after the earnings announcement day. We multiply the change by -1 such that a positive (negative) change is associated with increased optimism (pessimism).

We run the Fama-MacBeth regression for average recommendation changes of analysts during the subsequent three weeks after the earnings announcement:

$$\begin{aligned} RecChng_{i,t+b:t+d} =& \gamma_{0,t} + \gamma_{reg,t} REG_{i,t} + \gamma_{afe,t} AFE_{i,t} + \\ & \gamma_{dgtw,t} DGTW_{i,t} + \sum_{k=1}^{K} \gamma_{k,t} CONTROLS_{k,i,t} + \epsilon_{i,t}, \end{aligned} \tag{IA.2}$$

where $RecChng_{i,t+b:t+d}$ denotes the average of recommendation changes issued by analysts from b days ahead to d days ahead of the earnings announcement day t in quarter q. We include the standard set of controls for firm characteristics as in Section 4.1. In the second stage of the Fama-MacBeth procedure, we compute time-series value-weighted averages of coefficients based on the daily number of cross-sectional observations.

Table IA.13 reports the regression results. Similar to the findings documented for *AFE* and *RetForeErr*, *RecChng* also tends to be more positive following a positive *REG*. This result provides additional support for the notion that analysts revise their expectations based on the market reaction to earnings information, and a market misreaction would lead to a distortion in analyst expectation formation.

IA.7 Alternative Explanations: Analyst Incentives, Soft Information, and Additional Fundamental Information

In this section, we first investigate whether the predictive effect of *REG* on *AFE* and *SYY* is more pronounced for positive or negative *REG*, and find that the effect is statistically significant and of similar economic magnitude on both sides. Second, we show that controlling for "soft" information based on textual measures of the earnings calls' management and Q&A transcripts using the Loughran and McDonald dictionary (Loughran and McDonald, 2016) does not affect our main findings. Third, we analyze the role of additional fundamental information released on earnings days (following Hand et al., 2022), specifically the sales surprise, and find that including sales forecast errors in our regressions does not alter our main findings.

IA.7.1 Positive and Negative REG

As evidenced in the extant literature, analysts may have incentives to be optimistic, as they are more likely to experience favorable job separations in that case (Hong and Kubik, 2003). Similarly, investor optimism can induce stock misvaluation to a greater extent than pessimism due to restrictions on short-selling stocks (Stambaugh et al., 2012). Thus, we examine whether the effect of REG on various variables is concentrated on one side. Table IA.14 reports the results.

We find that the positive impact of REG on next quarter's AFE is not dominated by either positive or negative REG. For example, the difference between the coefficients for positive and negative REG of 0.52 in column (4) is not statistically significant (t-statistics of 1.33).

For the effect of REG on SYY, it is clearly shown that the coefficients on both the positive and negative REG interaction terms are positive and statistically significant, which means that the positive influence of REG on SYY is not driven solely by positive or negative REG. Interestingly, the difference between the REG coefficient estimates of 1.281 in column (7) is statistically significant (t-statistics of 3.46), in line with Stambaugh et al. (2012)'s findings.

IA.7.2 Effect of REG *on* AFE *and* SYY*: Controlling for Soft Information*

We further extend the analysis from Table 4 (AFE) and Table 5 (SYY) by controlling for text-based measures derived from earnings call transcripts in our regressions. Specifically, we construct textual measures based on the management and Q&A transcripts using the Loughran and McDonald dictionary (Loughran and McDonald, 2016), including the difference between the number of positive and negative words scaled by their sum (*Tone*) and the fraction of uncertainty words (*Uncertainty*). We show that including these measures does not affect our main findings. The results are reported in Table IA.15.

IA.7.3 Effect of REG *on* AFE *and* SYY*: Controlling for Additional Fundamental Information*

Moreover, we extend the analysis from Table 4 (AFE) and Table 5 (SYY) by controlling for additional fundamental information besides earnings that is released on earnings days. Specifically, Hand et al. (2022) find that earnings guidance and analyst sales forecast errors are found to be the most important releases besides earnings. We analyze the role of earnings guidance in detail in Section 6.3 of the paper. Furthermore, Tables IA.16 and IA.17 control for sales surprises and show that including this variable does not affect our main findings.

IA.8 REG *and Anomaly Returns: Additional Tests*

Table IA.18 repeats the analysis conducted in Table 7 for selected individual anomalies. The reported coefficient estimates correspond to the graphs depicted in Figure 3.

Table IA.19 repeats the analysis conducted in Table 7, where *REG* is replaced with *DGTW*.

Table IA.20 repeats the analysis conducted in Table 7, where *REG* is replaced with *SUE*.

IA.9 Impact of Global Analyst Research Settlement

In this section, we investigate the predictive relation of *REG* to *AFE* around the Global Analyst Research Settlement event (Global Settlement, GS), which attempted to reduce conflicts of interest by limiting the connections between research and investment banking departments. The settlement was instantiated in 2002 and ten of the US top investment firms were affected. With the cutting of ties with the investment banking department, GS-affected analysts' ability to solicit information was significantly reduced (especially private information about firms through the investment banking department), likely making them more reliant on public signals like market reactions. Guided by this intuition, we conjecture that firms covered by more GS-affected analysts would present a stronger reaction of *AFE* to *REG* after the Global Settlement.

Note that while the GS directly affects the information environment of analysts, our goal is to measure an impact of this change on the extent to which analysts are influenced by biased public signals in their expectations formation process. Due to the indirectness of this effect (i.e., through an additional interaction), we do not expect the highest level of statistical power in this part of our analysis and mainly focus on the consistency of the observed impact with our hypothesis. With these caveats in mind, we test the influence of the Global Settlement on the sensitivity of *AFE* to *REG* by defining the three years before 2002 as the "PRE" GS period and the three years after as "POST". We first compute the percentage of GS-affected analysts for each firm-quarter in the "PRE" and "POST" years and focus on firms that are consistently ranked as above (or below) the cross-sectional median in terms of the percentage of GS-affected analysts. We identify the treated firms ("GS" firms) as firms that consistently have above-the-median percentages of GS-affected analysts, and those with below-the-median percentages as the control firms ("NonGS" firms).

Column (1) of Table IA.21 verifies that our baseline result of *REG* predicting *AFE* holds in the restricted sample period around the Global Settlement event. Next, we turn to the influence of the Global Settlement. Column (2) presents the response to *REG* for the different subgroups PRE-NonGS, PRE-GS, POST-NonGS, and POST-GS. The comparison between the coefficients on *REG* for the PRE-GS and PRE-NonGS subgroups suggests that firms of both subgroups react to *REG* to a similar extent before the Global Settlement is substantiated — if anything, the response is slightly stronger in the NonGS-subgroup. In contrast, the firms with more GS-affected analysts (that is, the GS-subgroup) respond much more strongly to *REG* compared to the NonGS-subgroup after the Global Settlement took effect. This change is reflective of an increase in GS-affected analysts' reliance on public signals when their access to information via the investment banking department is restricted. Column (3) presents the result of a difference-in-differences regression. The positive and statistically significant coefficient (at the 10% level) on the triple interaction term $REG \times POST \times GS$ confirms the result of the subgroup analysis and demonstrates that the effect of *REG* on one-quarter-ahead *AFE* gets stronger for firms with more GS-affected analysts after the Global Settlement.

IA.10 Cross-Firm Heterogeneity

In this section, we extend the analysis conducted in Table 10 (firm heterogeneity, information environment, and mispricing) and consider additional firm characteristics that are associated with the quality of investors' public or private information. We consider four cross-sectional subsamples based on the monthly stock-level medians of (i) analyst coverage, (ii) firm market cap, (iii) institutional ownership, and (iv) analyst disagreement. The results are presented in Table IA.22.

The first set of results indicates that analyst coverage is relevant for the cross-sectional relation between REG and SYY's mispricing scores. The effect is both statistically and economically significant. For example, in quarter $q+1$, firms with below-median analyst coverage exhibit a 47% (= 0.825/1.769) higher sensitivity of SYY to REG. The effect is also stronger for small firms, consistent with lower analyst and media coverage, but the effect is weaker (a 31% (= 0.651/2.092) increase in sensitivity in quarter $q+1$). The third set of results indicates that the institutional clientele base is also an important determinant. Not surprisingly, firms with a lower institutional base are more prone to mispricing, which results in a higher sensitivity of SYY to REG. The effect reaches its peak after four quarters, where firms with below-median institutional ownership present a 50% (= 1.050/2.110) higher sensitivity of SYY to REG. Finally, the fourth set of tests reveals that firms with higher analyst dispersion present a 104% higher sensitivity to REG in quarter q+1. If analyst dispersion also reflects the difference of opinions across market participation, this finding is in line with Miller's (1977) argument.

In sum, the collective set of results shows that REG contributes to the perpetuation of mispricing most strongly for firms for which market participants, and analysts in particular, do not have very strong private and public information.

IA.11 Confirmation Bias and Amplification Effect

We provide additional details on the analysis of a confirmation bias in the relation between REG and analyst forecast errors (AFE), as well as an amplification effect between REG and AFE when predicting SYY mispricing scores, as described in in Section 6.4.

For the analysis of a potential confirmation bias between investors and analysts captured by REG and AFE being in the same direction, we broadly follow Pouget et al. (2017), employing a linear probability model. In particular, we estimate daily Fama-MacBeth regressions using the following specification:

$$
\begin{aligned}
D(AFE_{i,q} \ \& \ AFE_{i,q+n} \text{ Same Sign}) \ &= \ \gamma_{0,t} + \gamma_{1,t} D(AFE_{i,q} \ \& \ REG_{i,q} \text{ Same Sign}) \\
&+ \gamma_{2,q} D(AFE_{i,q} \ \& \ AFE_{i,q-1} \text{ Same Sign}) + \gamma_{afe,t} AFE_{i,t} + \gamma_{dgtw,t} DGTW_{i,t} \\
&+ \gamma_{syy,t} SYY_{i,t} + \sum_{k=1}^{K} \gamma_{k,t} CONTROLS_{k,i,t} + \epsilon_{i,t}.
\end{aligned} \tag{IA.3}
$$

The dependent dummy variable D(AFE_q & AFE_{q+n} Same Sign) captures whether AFE in the current quarter and in a future quarter are of the same sign, and the main explanatory variable is the amplification dummy D(Amplification)=D(AFE_q & REG_q Same Sign) described in the main text. We include our standard set of controls as well as another dummy variable D(AFE_q & AFE_{q-1} Same Sign) that accounts for the natural persistence in AFE. This dummy is equal to one when AFE_q is in the same direction as AFE_{q-1}. Overall, the regression results reveal whether the next quarter's AFE has a higher likelihood of being in the same direction as current AFE when current AFE and REG are in the same direction.

For the analysis of an amplification effect between REG and AFE when predicting SYY mispricing scores, we extend the Fama-MacBeth regression from equation (6) by including the amplification dummy and interacting it with REG:

$$
\begin{aligned}
SYY_{i,m+n} \ &= \gamma_{0,m} + \gamma_{reg\_amp,m} REG_{i,m} \times D(\text{Amplification})_i + \gamma_{reg,m} REG_{i,m} \\
&+ \gamma_{amp,m} D(\text{Amplification})_i + \gamma_{afe,m} AFE_{i,m} + \gamma_{dgtw,m} DGTW_{i,m} \\
&+ \gamma_{syy,m} SYY_{i,m} + \sum_{k=1}^{K} \gamma_{k,m} CONTROLS_{k,i,m} + \epsilon_{i,m}.
\end{aligned} \tag{IA.4}
$$

The coefficient $\gamma_{reg,m}$ captures the impact of REG on SYY without any amplification between REG and AFE. On the other hand, $\gamma_{reg\_amp,m}$ reflects the additional effect of REG on SYY when REG and AFE are in the same direction and there is an amplification effect. We include our standard set of controls into the regression.

IA.12 Impulse Response Functions

We finally examine the dynamic relation between REG, AFE, and SYY by estimating a quarterly vector autoregression (VAR) system of these variables and analyzing the corresponding impulse response functions. We consider four lags of each variable. The regressions include the full set of firm control variables together with firm fixed effects and quarter fixed effects. Each graph in Figure IA.2 plots the response of AFE, SYY, and REG to shocks in the other two variables in the subsequent $0, 1, 2, \ldots, 12$ quarters, respectively.

The first graph in Figure IA.2 depicts the response of AFE to a one-standard-deviation shock in REG and SYY. As shown in the plot, both REG and SYY positively affect AFE in the following quarters. The impulse responses also confirm the result from our regression analysis that the effect of REG on AFE is much larger in magnitude compared to the effect of SYY. Precisely, a one-standard-deviation shock to REG leads to a nearly five times larger response of AFE than a one-standard-deviation shock to SYY. Next, the response of SYY to shocks in REG and AFE is shown in the second graph. Again, the impulse responses clearly confirm that while SYY reacts positively to a one-standard-deviation shock in both REG and AFE, the impact of REG is much larger than that of SYY. These results provide further supporting evidence for the economic importance of REG for future analyst forecast errors and mispricing.

The last graph shows the response of REG to shocks in AFE and SYY. A shock to both AFE and SYY leads to a positive response in REG in the following quarters, indicating that a stock with greater AFE and SYY is exposed to a more pronounced REG in the future. Overall, the VAR results highlight the importance of REG even after controlling for lagged effects of other variables, and support the notion of a dynamic amplification effect between REG, AFE, and SYY.

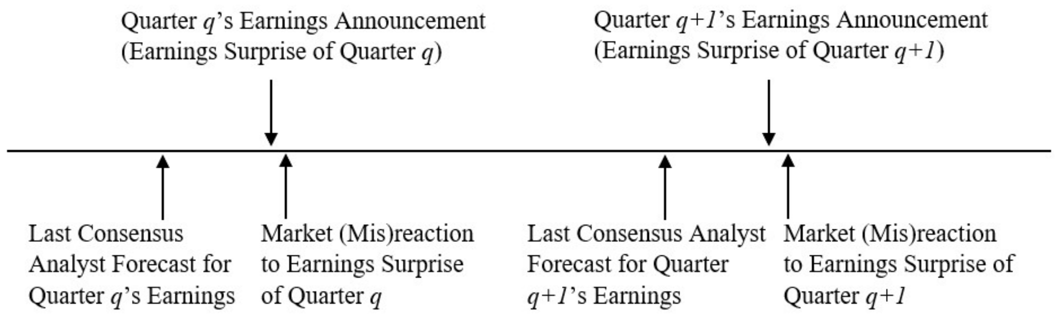


Fig. IA.1 – Timeline of Earnings Announcements, *REG*, and *AFE*

The figure illustrates the timeline of earnings announcements, analyst forecasts, and *REG* for two consecutive quarters. Analysts maintain forecasts in quarter q for the upcoming quarter-q earnings announcement. The quarter-q analyst forecast error (AFE) is determined ex-post after quarter-q earnings are announced. The Return-Earnings Gap (REG) in quarter q is computed based on the earnings day market reaction to the earnings announcement in quarter q and the earnings surprise (SUE). One main result of this paper is that quarter-$q+1$ analyst forecast errors are predicted by quarter-q REG, controlling for quarter-q analyst forecast errors and other variables.

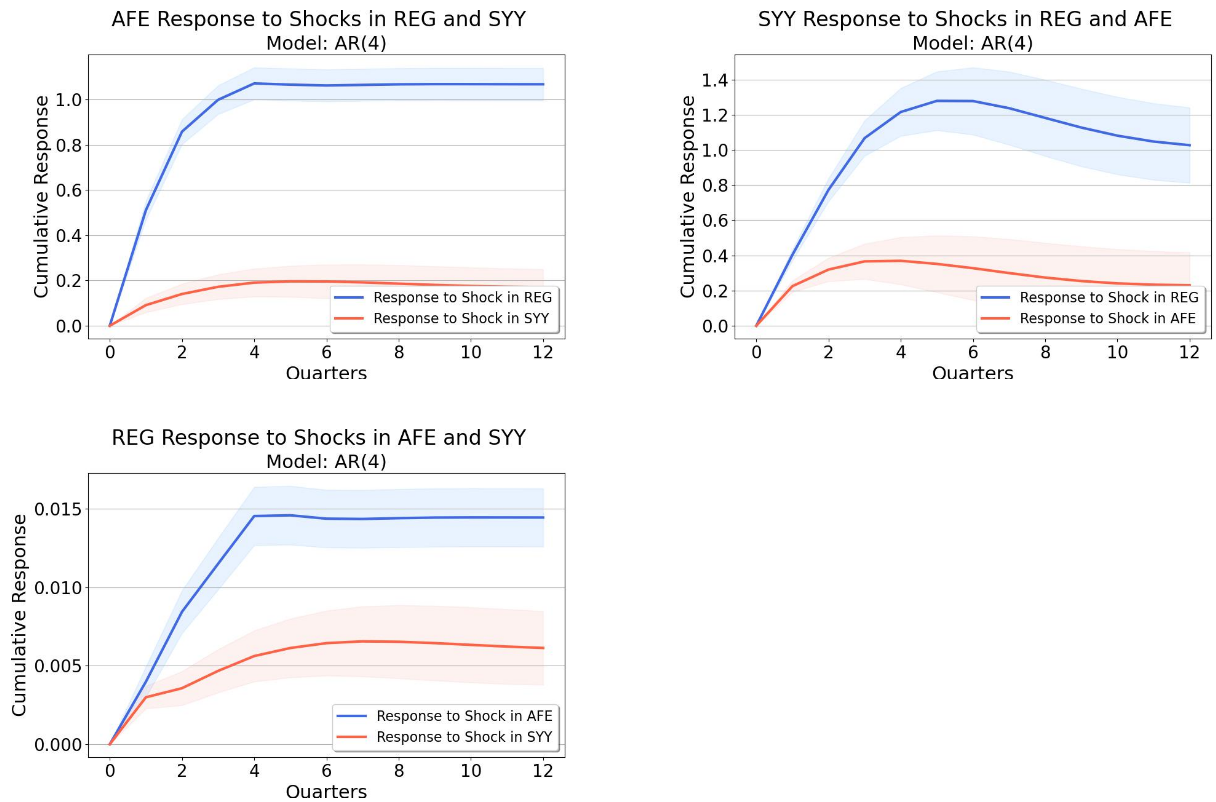


Fig. IA.2 – Impulse Responses of AFE, SYY, and REG

$$\begin{aligned}
AFE_{i,q} = \quad & \alpha_1 + \sum_{j=1}^{4} \beta_{1,j} \cdot AFE_{i,q-j} + \sum_{j=1}^{4} \gamma_{1,j} \cdot SYY_{i,q-j} + \sum_{j=1}^{4} \theta_{1,j} \cdot REG_{i,q-j} + \delta \cdot X_{i,q-1} + f_i + q_t + \epsilon_{1,i,q}; \\
SYY_{i,q} = \quad & \alpha_2 + \sum_{j=1}^{4} \beta_{2,j} \cdot AFE_{i,q-j} + \sum_{j=1}^{4} \gamma_{2,j} \cdot SYY_{i,q-j} + \sum_{j=1}^{4} \theta_{2,j} \cdot REG_{i,q-j} + \delta \cdot X_{i,q-1} + f_i + q_t + \epsilon_{2,i,q}; \\
REG_{i,q} = \quad & \alpha_3 + \sum_{j=1}^{4} \beta_{3,j} \cdot AFE_{i,q-j} + \sum_{j=1}^{4} \gamma_{3,j} \cdot SYY_{i,q-j} + \sum_{j=1}^{4} \theta_{3,j} \cdot REG_{i,q-j} + \delta \cdot X_{i,q-1} + f_i + q_t + \epsilon_{3,i,q}.
\end{aligned}$$

The figures show the impulse responses of AFE, SYY, and REG, respectively, to a one-standard-deviation shock to the other two variables. We estimate a quarterly vector autoregression (VAR) system of AFE, SYY, and REG, with four lags of each variable. The regressions include the full set of firm control variables ($X_{i,q-1}$) together with firm fixed effects (f_i) and quarter fixed effects (q_t). The VAR system takes the form as shown in the above equation system. For the computation of impulse responses, variables are ordered in such way that the time-0 effect is set to zero. The solid lines depict the variable responses, and the shaded areas depict 90% confidence intervals. The sample period is from January 1985 to December 2018.

Table IA.1 – Variable Definition

This table provides definitions for the main variables in our analysis.

Variable	Definition
DGTW	Characteristic-adjusted daily stock return constructed following Daniel et al. (1997), calculated by subtracting the return on a peer portfolio consisting of stocks with similar size, book-to-market ratio, and past return momentum.
SUE	The difference between actual EPS and the median of analysts' estimated EPS scaled by the standard deviation of analysts' forecasts (adjusted for dividends and stock splits).
AdjSUE	The residual from a regression of *SUE* on *LnSIZE*, *LnBM*, as well as day-of-week and month-of-year fixed effects.
REG	The difference in the rankings of *DGTW* and *AdjSUE* of the stock on earnings announcement day t.
AFE	Analyst earnings forecast errors. The difference between the median of analysts' estimated EPS and the actual EPS, scaled by the standard deviation of analysts' forecasts (adjusted for dividends and stock splits).
RetForeErr	Analyst price-target-based return forecast error (in %). The average of the return forecast errors across analysts issuing price targets over the subsequent 60 days following an earnings announcement. An analyst return forecast error is defined as ((Future price target−Actual future price)/Current price)−1.
RecChng	The average recommendation change issued by analysts, multiplied by −1.
SYY	Monthly composite mispricing score of Stambaugh et al. (2015).
InstDirTrd	Institutional investors' daily shares bought minus shares sold normalized by total daily stock volume (in %).
LnSIZE	The natural log of the firm size.
LnBM	The natural log of the firm book-to-market ratio.
RET5	Cumulative stock return over the past 5 trading days (in %).
RET21	Cumulative stock return over the past 21 trading days (in %).
MOM	Momentum. The average of daily returns over the period from t-252 to t-21 (in %).
RVOL	Realized volatility of stock. The square root of the annualized realized variance, which is 252 times the average of squared daily returns over the past 21 trading days.
ILLIQ	Amihud (2002) illiquidity measure. The average ratio of absolute daily return and daily total dollar trading volume of a stock over the past 21 trading days.
DISP	Dispersion of analysts' earnings forecasts. The standard deviation of analysts' earnings forecasts scaled by the stock price.
NUMEST	The natural logarithm of one plus the number of analysts issuing earnings forecasts.
MRET	Monthly cumulative return (in %).
MMOM	Monthly momentum. The cumulative monthly return over the past 11 months (in %).
MRVOL	Monthly realized volatility. The standard deviation of monthly returns over the 12 months ending in each June; if at least 9 monthly returns available, then apply the *MRVOL* to the following 12 months (i.e., from July of the same year to June of the next year).
MILLIQ	Monthly illiquidity. The average daily Amihud (2002) illiquidity ratio over all trading days during the month.

Table IA.2 – *REG*, *DGTW*, *SUE*, and Subsequent Abnormal Returns

This table reports the average DGTW-adjusted abnormal returns (expressed in percent) on the earnings day t and cumulative DGTW-adjusted abnormal returns from day $t+1$ to day $t+n$ ($n = 21, 63, 126, 252, 504, 756$) of the high-minus-low decile portfolios of stocks single-sorted by *REG*, *DGTW*, and *SUE* on day t. The sample period is from January 1985 to December 2018. We report value-weighted time-series averages of the cross-sectional regression estimates based on the daily number of cross-sectional observations. t-statistics based on Newey-West standard errors are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	(1) t	(2) t+1:t+21	(3) t+1:t+63	(4) t+1:t+126	(5) t+1:t+252	(6) t+1:t+504	(7) t+1:t+756
			HML Spread of Decile Portfolios Single-Sorted on REG				
DGTW	10.40***	-1.03***	-1.51***	-1.82***	-2.22***	-3.95***	-5.66***
	(115.47)	(-6.65)	(-5.30)	(-3.79)	(-3.31)	(-3.60)	(-4.68)
			HML Spread of Decile Portfolios Single-Sorted on DGTW				
DGTW	22.57***	1.44***	2.57***	2.70***	2.71***	2.78***	3.02***
	(125.50)	(7.71)	(8.07)	(5.21)	(4.03)	(3.47)	(3.68)
			HML Spread of Decile Portfolios Single-Sorted on SUE				
DGTW	6.07***	2.80***	4.18***	4.57***	5.19***	6.66***	8.16***
	(54.39)	(12.77)	(9.62)	(7.33)	(5.94)	(6.28)	(19.82)

Table IA.3 – Predicting *AFE*: Monthly and Quarterly Aggregation of Observations

This table reports the results from monthly (Panel A) and quarterly (Panel B) Fama-MacBeth cross-sectional regressions of *AFE* in quarters $q+1$ to $q+12$ on *REG* and other explanatory variables (*AFE*, *DGTW*, and *SYY*) in quarter q. *AFE*, *DGTW*, and *SYY* are analyst forecast errors, earnings announcement day DGTW-adjusted abnormal returns, and firms' Stambaugh et al. (2015) score. Firm control variables include *LnSIZE*, *LnBM*, *RET5*, *RET21*, *MOM*, *RVOL*, *ILLIQ*, *DISP*, and *NUMEST*. The sample period is from January 1985 to December 2018. We report value-weighted time-series averages of the cross-sectional regression estimates based on the monthly (Panel A) and quarterly (Panel B) number of cross-sectional observations. An overview of all variable definitions and descriptions is provided in Internet Appendix Table IA.1. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Monthly Fama-MacBeth Cross-Sectional Regressions

	(1) AFE_{q+1}	(2) AFE_{q+1}	(3) AFE_{q+1}	(4) AFE_{q+1}	(5) AFE_{q+1}	(6) AFE_{q+1}
REG	3.021***	1.912***	1.727***	1.718***	1.474***	1.425***
	(14.22)	(7.58)	(6.23)	(8.50)	(6.54)	(8.05)
AFE	0.089***	0.076***	0.070***	0.052***	0.041***	0.024***
	(8.42)	(6.8)	(5.40)	(5.09)	(4.99)	(3.75)
DGTW	-0.089***	-0.057***	-0.056***	-0.051***	-0.039***	-0.032***
	(-12.02)	(-6.03)	(-3.93)	(-8.20)	(-6.17)	(-5.82)
SYY	0.018***	0.020***	0.020***	0.018***	0.018***	0.018***
	(10.52)	(10.29)	(9.75)	(9.52)	(8.12)	(9.36)
Adj. R-Squared	4.73%	3.83%	3.26%	2.36%	2.21%	1.17%
#Months	286	285	286	286	283	273
#Obs	172,926	168,681	165,079	162,126	150,073	134,978

Panel B: Quarterly Fama-MacBeth Cross-Sectional Regressions

	(1) AFE_{q+1}	(2) AFE_{q+1}	(3) AFE_{q+1}	(4) AFE_{q+1}	(5) AFE_{q+1}	(6) AFE_{q+1}
REG	3.197***	2.095***	1.612***	1.820***	1.438***	1.381***
	(14.59)	(7.39)	(4.51)	(9.17)	(6.28)	(6.68)
AFE	0.078***	0.062***	0.075***	0.044***	0.043***	0.023***
	(7.55)	(4.63)	(4.17)	(4.96)	(4.29)	(3.06)
DGTW	-0.094***	-0.063***	-0.049**	-0.054***	-0.035***	-0.033***
	(-11.88)	(-5.62)	(-2.51)	(-8.85)	(-5.53)	(-5.51)
SYY	0.019***	0.021***	0.021***	0.020***	0.019***	0.019***
	(10.89)	(10.83)	(9.82)	(9.97)	(7.93)	(10.01)
Adj. R-Squared	3.99%	3.2%	2.71%	1.85%	2.24%	1.08%
#Qtrs	127	127	127	127	127	123
#Obs	172,926	168,681	165,079	162,126	150,073	134,978

Table IA.4 – Anomaly Dissection: Management and Performance Anomalies

This table lists the 11 anomalies based on which the Stambaugh et al. (2015) SYY composite score is constructed. According to Stambaugh and Yuan (2017), the 11 anomalies can be clustered into two classes: Management and Performance. For each anomaly, we present the associated class and name adopted by Stambaugh and Yuan (2017). The column "Closest Match" indicates the closest match available from Chen and Zimmermann's Open Source Cross-Sectional Asset Pricing database. The last column "Sign" flags the direction of subsequent returns following a greater value of an anomaly, where "-1" implies return reversal and "1" suggests return continuation.

Classification	Predictor	Closest Match	Sign
Management	Asset Growth	AssetGrowth	-1
Management	Composite Equity Issues	CompEquIss	-1
Management	Investment to Assets	Investment	-1
Management	Net Stock Issues	NetEquityFinance	-1
Management	Accruals	Accruals	-1
Management	Net Operating Assets	NOA	-1
Performance	Distress	FailureProbability	-1
Performance	O-score	OScore	-1
Performance	Gross Profitability	GP	1
Performance	Momentum	Mom12m	1
Performance	Return on Assets	roaq	1

Table IA.5 – REG and Raw Values of SYY's Anomaly-Related Characteristics

This table presents the coefficients on REG from monthly Fama-MacBeth cross-sectional regressions of raw values of SYY's anomaly-related characteristics in months $m+3$ to $m+36$ on REG and other explanatory variables (AFE, $DGTW$, and the raw characteristic) in month m. For easier readability, the raw values of each characteristic are multiplied by 100. Panel A reports the results for management-related variables, and Panel B reports the results for performance-related variables. Firm control variables include *LnSIZE*, *LnBM*, *MRET*, *MMOM*, *MRVOL*, and *MILLIQ*. All variables except for REG, AFE, and $DGTW$ are observed at the end of the month of the earnings announcement. The sample period is from January 1985 to December 2018. We report value-weighted time-series averages of the cross-sectional regression estimates based on the number of cross-sectional observations. Details of individual anomalies can be found in Table IA.4. An overview of all variable definitions and descriptions is provided in Internet Appendix Table IA.1. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Management

	(1) $m+3$	(2) $m+6$	(3) $m+9$	(4) $m+12$	(5) $m+24$	(6) $m+36$
Accruals	0.365***	0.350***	0.289*	-0.137	-0.759***	-0.655***
	(3.33)	(2.72)	(1.91)	(-0.76)	(-4.15)	(-3.33)
Growth	0.299	0.348	0.683	0.811	-3.152***	-2.313**
	(0.52)	(0.46)	(0.72)	(0.74)	(-3.38)	(-2.28)
CompEquIss	4.056	5.950	11.164**	7.659	12.224*	23.703***
	(1.37)	(1.42)	(1.99)	(1.14)	(1.86)	(4.96)
Inv	2.558***	2.488**	5.475***	7.097***	-1.539	-2.421
	(2.80)	(2.39)	(4.44)	(5.40)	(-0.94)	(-1.42)
NetStkIss	-0.129	0.068	0.157	0.565**	0.549**	0.639**
	(-0.91)	(0.41)	(0.71)	(2.29)	(2.56)	(2.60)
NOA	1.334***	1.812**	2.999***	3.596***	1.415	2.239**
	(2.95)	(2.55)	(3.44)	(3.47)	(1.53)	(2.40)

Panel B: Performance

	(1) $m+3$	(2) $m+6$	(3) $m+9$	(4) $m+12$	(5) $m+24$	(6) $m+36$
Distress	2.836	40.021**	0.990	12.001	29.595*	6.457
	(0.16)	(2.20)	(0.06)	(0.74)	(1.92)	(0.44)
OScore	0.200	0.262	-0.098	-0.108	-0.182	-0.381
	(0.81)	(0.91)	(-0.26)	(-0.24)	(-0.36)	(-0.62)
GP	0.102	-0.250	0.212	-0.823	-2.754***	-1.044
	(0.20)	(-0.46)	(0.20)	(-0.73)	(-4.41)	(-1.64)
ROA	-0.741***	-0.428	-0.275	-0.467***	-0.627***	-0.538
	(-2.74)	(-0.94)	(-0.53)	(-3.44)	(-2.81)	(-1.42)
MOM	-5.440***	-9.734***	-9.18***	-5.804***	-3.436**	-1.245
	(-5.83)	(-7.53)	(-6.64)	(-3.97)	(-2.16)	(-0.86)

Table IA.6 – Alternative Specifications of *REG*

This table reports results of Fama-MacBeth cross-sectional regressions predicting *AFE* and *SYY* based on four alternative specifications of *REG*. In particular, *REG* is constructed based on the differences between the rankings of (i) 1-day *RET* and *SUE*, (ii) 5-day *DGTW* and *AdjSUE*, (iii) 21-day *DGTW* and *AdjSUE*, or (iv) 1-day *DGTW* and *AdjSUE* ranked into 100 bins instead of 1,000 bins. Panels A and B present the results for predicting *AFE* and *SYY* in the following quarters, respectively. Lagged dependent variables and stock control variables are included. The sample period is from January 1985 to December 2018. We report value-weighted time-series averages of the cross-sectional regression estimates based on the daily number of cross-sectional observations. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Predicting AFE *in the Following Quarters*

	AFE_{q+1} (1)	AFE_{q+2} (2)	AFE_{q+3} (3)	AFE_{q+4} (4)	AFE_{q+8} (5)	AFE_{q+12} (6)
			SUE, 1-day RET			
REG	2.545***	1.653***	1.330***	1.431***	1.177***	1.123***
	(12.57)	(7.03)	(5.11)	(5.54)	(4.61)	(4.69)
AFE	0.131***	0.099***	0.077***	0.072***	0.067***	0.040***
	(13.07)	(8.44)	(6.21)	(5.71)	(5.12)	(3.35)
SYY	0.016***	0.020***	0.017***	0.015***	0.017***	0.016***
	(9.77)	(8.70)	(9.05)	(8.42)	(7.85)	(8.17)
			AdjSUE, 5-day DGTW			
REG	2.655***	1.779***	1.686***	1.551***	1.331***	0.914***
	(11.39)	(7.23)	(5.72)	(5.78)	(4.83)	(3.50)
AFE	0.125***	0.089***	0.064***	0.066***	0.054***	0.043***
	(11.98)	(7.00)	(5.10)	(5.06)	(3.95)	(3.32)
SYY	0.015***	0.020***	0.017***	0.016***	0.017***	0.016***
	(9.64)	(8.88)	(9.06)	(8.79)	(8.26)	(7.61)
			AdjSUE, 21-day DGTW			
REG	2.888***	1.740***	1.714***	1.760***	1.316***	0.730***
	(12.54)	(7.09)	(5.95)	(5.91)	(5.02)	(2.83)
AFE	0.111***	0.092***	0.067***	0.055***	0.052***	0.056***
	(10.38)	(7.06)	(5.42)	(3.84)	(3.61)	(4.31)
SYY	0.016***	0.020***	0.017***	0.015***	0.018***	0.015***
	(9.75)	(8.90)	(9.34)	(8.75)	(8.14)	(7.72)
			AdjSUE, 1-day DGTW; 100 bins			
REG	2.488***	1.618***	1.347***	1.474***	1.155***	0.937***
	(12.01)	(7.17)	(5.07)	(5.68)	(4.31)	(3.92)
AFE	0.134***	0.096***	0.077***	0.070***	0.068***	0.043***
	(13.45)	(8.37)	(6.28)	(5.64)	(5.62)	(3.61)
SYY	0.015***	0.020***	0.017***	0.015***	0.017***	0.016***
	(9.58)	(8.78)	(9.03)	(8.64)	(7.95)	(7.76)

Panel B: Predicting SYY *in the Following Quarters*

	SYY_{m+3} (1)	SYY_{m+6} (2)	SYY_{m+9} (3)	SYY_{m+12} (4)	SYY_{m+24} (5)	SYY_{m+36} (6)
			SUE, 1-day RET			
REG	2.431***	3.171***	3.259***	2.913***	1.176***	0.867**
	(11.73)	(12.05)	(10.85)	(9.16)	(3.14)	(2.45)
AFE	0.057***	0.026***	0.035***	0.025**	0.021**	0.020**
	(9.81)	(3.57)	(4.13)	(2.24)	(2.04)	(2.05)
SYY	0.841***	0.768***	0.661***	0.559***	0.463***	0.409***
	(86.00)	(73.35)	(64.62)	(112.70)	(84.03)	(69.58)
			AdjSUE, 5-day DGTW			
REG	2.249***	2.907***	2.882***	2.307***	1.461***	0.758**
	(9.84)	(9.86)	(8.68)	(6.40)	(3.74)	(2.06)
AFE	0.059***	0.027***	0.037***	0.030**	0.011	0.017*
	(9.34)	(3.47)	(3.97)	(2.59)	(1.08)	(1.8)
SYY	0.841***	0.769***	0.662***	0.559***	0.463***	0.409***
	(86.12)	(73.52)	(64.59)	(112.3)	(84.39)	(69.79)
			AdjSUE, 21-day DGTW			
REG	1.682***	2.352***	2.388***	1.762***	1.082***	0.800***
	(7.37)	(7.88)	(7.20)	(4.85)	(2.61)	(2.16)
AFE	0.065***	0.033***	0.042***	0.038***	0.021**	0.017*
	(10.62)	(4.34)	(4.63)	(3.35)	(2.00)	(1.76)
SYY	0.841***	0.768***	0.661***	0.558***	0.463***	0.409***
	(86.39)	(73.57)	(64.43)	(112.51)	(84.03)	(70.21)
			AdjSUE, 1-day DGTW; 100 bins			
REG	2.282***	2.915***	2.974***	2.628***	1.075***	0.595*
	(11.07)	(11.36)	(10.00)	(8.62)	(2.9)	(1.79)
AFE	0.059***	0.030***	0.040***	0.030***	0.023**	0.024**
	(9.91)	(4.21)	(4.65)	(2.81)	(2.22)	(2.52)
SYY	0.841***	0.769***	0.662***	0.559***	0.463***	0.409***
	(86.00)	(73.43)	(64.64)	(112.70)	(84.00)	(69.6)

Table IA.7 – Pre-2001 vs. Post-2002

This table reports results from Fama-MacBeth cross-sectional regressions predicting AFE in quarter $q+1$ and SYY in month $m+3$ for the subsample ending in 2001 and the subsample starting in 2002. Columns (1) to (4) show the results for predicting AFE in the next quarter. Columns (5) to (8) report the results for predicting SYY in the next quarter (i.e., three months ahead). We report value-weighted time-series averages of the cross-sectional regression estimates based on the daily number of cross-sectional observations. The sample period is from January 1985 to December 2018. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	AFE_{q+1}				SYY_{m+3}			
	Pre-2001		Post-2002		Pre-2001		Post-2002	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
REG	2.158***	2.24***	2.806***	2.730***	3.290***	2.374***	3.630***	2.338***
	(6.48)	(6.83)	(10.90)	(10.51)	(14.62)	(7.81)	(14.45)	(7.67)
AFE	0.165***	0.162***	0.118***	0.112***		0.054***		0.064***
	(9.15)	(8.97)	(10.39)	(10.12)		(5.57)		(7.95)
$DGTW$	-0.099***	-0.102***	-0.062***	-0.061***	-0.149***	-0.121***	-0.086***	-0.059***
	(-5.55)	(-5.62)	(-10.03)	(-9.66)	(-10.57)	(-8.58)	(-10.63)	(-6.65)
SYY		0.008***		0.020***	0.837***	0.838***	0.846***	0.846***
		(3.52)		(9.37)	(59.05)	(59.12)	(61.06)	(61.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	10.11%	9.95%	8.42%	8.76%	75.68%	75.75%	77.26%	77.3%
#Days/#Months	1,206	1,142	1,361	1,114	112	111	85	85
#Obs	78,282	74,870	114,360	91,501	61,035	61,035	63,381	63,381

Table IA.8 – Panel Regressions

This table reports the results from panel regressions of AFE in quarter $q+1$ and SYY in month $m+3$ on quarter-q (month-m) REG and other explanatory variables. Columns (1) and (2) show the results for predicting AFE in the next quarter. Columns (3) and (4) report the results for predicting SYY in the next quarter (i.e., three months ahead). The sample period is from January 1985 to December 2018. All regressions include firm and time fixed effects. Standard errors are clustered on firm and time. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	AFE in the Next Quarter		SYY in the Next Quarter	
	(1)	(2)	(3)	(4)
REG	2.401***	2.410***	0.736***	2.190***
	(16.40)	(16.83)	(4.47)	(10.79)
AFE	0.023***	0.025***	0.085***	0.056***
	(3.57)	(3.58)	(11.80)	(9.00)
$DGTW$	-0.060***	-0.066***		-0.072***
	(-14.36)	(-16.79)		(-8.04)
SYY		0.009***	0.719***	0.718***
		(5.76)	(45.01)	(44.92)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Firm, Time	Firm, Time	Firm, Time	Firm, Time
Adj. R-squared	9.82%	9.44%	76.75%	76.80%
#Obs	198,351	171,301	128,878	128,878

Table IA.9 – The Effect of REG on AFE and SYY: Excluding REG's Components

This table repeats the analysis conducted in Table 4 (for AFE) and Table 5 (for SYY) excluding AFE and $DGTW$ as explanatory variables. Panel A reports the results for AFE, and Panel B reports the results for SYY. An overview of all variable definitions and descriptions is provided in Internet Appendix Table IA.1. The sample period is from January 1985 to December 2018. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Predicting AFE

	(1) AFE_{q+1}	(2) AFE_{q+2}	(3) AFE_{q+3}	(4) AFE_{q+4}	(5) AFE_{q+8}	(6) AFE_{q+12}
REG	2.562***	1.881***	1.603***	1.564***	1.447***	1.111***
	(20.41)	(13.23)	(12.96)	(12.26)	(10.37)	(8.39)
SYY	0.018***	0.020***	0.017***	0.017***	0.018***	0.017***
	(10.74)	(8.89)	(9.52)	(9.08)	(8.66)	(8.73)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-Squared	5.31%	4.67%	4.13%	3.35%	3.25%	2.58%
#Days	2,473	2,452	2,429	2,410	2,327	2,185
#Obs	172,926	168,681	165,079	162,126	150,073	134,978

Panel B: Predicting SYY

	(1) SYY_{m+3}	(2) SYY_{m+6}	(3) SYY_{m+9}	(4) SYY_{m+12}	(5) SYY_{m+24}	(6) SYY_{m+36}
REG	1.948***	2.136***	2.49***	2.242***	1.106***	0.808***
	(15.44)	(12.72)	(12.48)	(9.97)	(3.81)	(2.94)
SYY	0.842***	0.770***	0.663***	0.560***	0.464***	0.41***
	(86.45)	(73.86)	(64.98)	(112.31)	(83.87)	(69.47)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-Squared	76.21%	62.59%	47.38%	35.86%	26.95%	22.6%
#Months	207	205	202	199	191	185
#Obs	129,589	125,581	122,006	118,183	106,572	95,984

Table IA.10 – Predicting AFE and SYY Without REG

This table repeats the analysis conducted in Table 4 (for AFE) and Table 5 (for SYY) excluding REG as an explanatory variable. Panel A reports the results for AFE, and Panel B reports the results for SYY. An overview of all variable definitions and descriptions is provided in Internet Appendix Table IA.1. The sample period is from January 1985 to December 2018. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Predicting AFE

	(1) AFE_{q+1}	(2) AFE_{q+2}	(3) AFE_{q+3}	(4) AFE_{q+4}	(5) AFE_{q+8}	(6) AFE_{q+12}
AFE	0.188***	0.142***	0.116***	0.108***	0.093***	0.069***
	(26.09)	(19.27)	(14.3)	(14.38)	(13.55)	(9.75)
$DGTW$	-0.021***	-0.009*	-0.012*	-0.010*	-0.007	0.000
	(-3.74)	(-1.89)	(-1.83)	(-1.87)	(-1.22)	(0.09)
SYY	0.017***	0.020***	0.017***	0.016***	0.018***	0.017***
	(10.62)	(8.78)	(9.09)	(9.10)	(8.23)	(8.60)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	8.39%	7.01%	5.89%	5.09%	4.43%	3.27%
#Days	2,433	2,411	2,393	2,379	2,289	2,130
#Obs	173,909	169,658	166,061	163,097	151,059	135,848

Panel B: Predicting SYY

	(1) SYY_{m+3}	(2) SYY_{m+6}	(3) SYY_{m+9}	(4) SYY_{m+12}	(5) SYY_{m+24}	(6) SYY_{m+36}
AFE	0.096***	0.079***	0.09***	0.074***	0.044***	0.037***
	(18.62)	(12.85)	(12.61)	(8.49)	(4.55)	(3.76)
$DGTW$	-0.029***	-0.023***	-0.009	-0.003	0.001	0.006
	(-5.6)	(-3.24)	(-1.14)	(-0.33)	(0.07)	(0.60)
SYY	0.841***	0.769***	0.663***	0.561***	0.464***	0.410***
	(86.71)	(74.26)	(65.52)	(113.36)	(84.29)	(69.80)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	76.25%	62.56%	47.44%	35.98%	26.99%	22.63%
#Months	207	206	205	200	194	186
#Obs	130,658	126,647	123,070	119,247	107,628	97,020

Table IA.11 – Predictive Results Including Firms with Non-December Fiscal Year Ends

This table repeats the analysis conducted in Table 4 (for AFE) and Table 5 (for SYY) based on a sample consisting of firms with all different fiscal year ends. Panel A reports the results for AFE, and Panel B reports the results for SYY. An overview of all variable definitions and descriptions is provided in Internet Appendix Table IA.1. The sample period is from January 1985 to December 2018. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A. Predicting AFE

	AFE_{q+1} (1)	AFE_{q+2} (2)	AFE_{q+3} (3)	AFE_{q+4} (4)	AFE_{q+8} (5)	AFE_{q+12} (6)
REG	2.540***	1.570***	1.266***	1.455***	1.200***	0.940***
	(12.3)	(6.91)	(4.81)	(5.57)	(4.59)	(4.00)
AFE	0.127***	0.098***	0.082***	0.071***	0.066***	0.044***
	(12.94)	(8.25)	(6.84)	(5.80)	(5.60)	(3.78)
$DGTW$	-0.081***	-0.046***	-0.045***	-0.042***	-0.034***	-0.012
	(-9.56)	(-5.64)	(-3.14)	(-4.90)	(-3.71)	(-1.46)
SYY	0.015***	0.020***	0.017***	0.016***	0.017***	0.017***
	(9.86)	(9.14)	(9.64)	(9.16)	(8.13)	(7.78)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-Squared	9.42%	7.52%	6.31%	5.79%	4.88%	3.47%
#Days	2,691	2,661	2,635	2,601	2,469	2,297
#Obs	201,939	197,128	193,187	189,809	176,545	159,758

Panel B. Predicting SYY

	SYY_{m+3} (1)	SYY_{m+6} (2)	SYY_{m+9} (3)	SYY_{m+12} (4)	SYY_{m+24} (5)	SYY_{m+36} (6)
REG	2.486***	2.999***	3.004***	2.629***	1.04***	0.476
	(12.67)	(12.21)	(10.77)	(9.29)	(3.11)	(1.54)
AFE	0.053***	0.027***	0.036***	0.026***	0.017*	0.021**
	(9.61)	(4.09)	(4.43)	(2.74)	(1.77)	(2.37)
$DGTW$	-0.093***	-0.100***	-0.088***	-0.065***	-0.018	0.004
	(-11.88)	(-9.38)	(-7.55)	(-5.11)	(-1.36)	(0.35)
SYY	0.840***	0.771***	0.667***	0.567***	0.471***	0.419***
	(100.96)	(87.47)	(76.93)	(124.8)	(93.67)	(74.67)
Adj. R-Squared	76.12%	62.78%	47.89%	36.77%	27.85%	23.45%
#Months	264	262	260	258	250	241
#Obs	151,267	146,637	142,527	138,166	124,819	112,713

Table IA.12 – *REG* and Analyst Price Target Forecast Errors

This table reports results from daily Fama-MacBeth cross-sectional regressions of analyst implied return forecast errors on *REG*. Analyst implied return forecast errors are based on their 12-month price targets, averaged over the subsequent 60 trading days (one quarter) after a firm's earnings announcement day. The sample includes 5,733 distinct stocks with valid analyst price targets (PTG) from January 2000 to December 2018. Column (1) presents the result based on all observations. Columns (2) and (3) show the results on the observations where we require at least two and three analysts, respectively, to issue future price targets (PTG) for the same stock. Firm control variables include *LnSIZE*, *LnBM*, *RET5*, *RET21*, *MOM*, *RVOL*, *ILLIQ*, and *NUMEST*. We report value-weighted time-series averages of the cross-sectional regression estimates based on the daily number of cross-sectional observations. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	All Obs	NumPTG⩾2	NumPTG⩾3
	(1)	(2)	(3)
REG	2.841**	3.267**	3.791
	(2.11)	(1.99)	(1.63)
AFE	0.061	0.142*	0.081
	(1.07)	(1.91)	(0.71)
DGTW	-0.448***	-0.411***	-0.421***
	(-12.93)	(-9.41)	(-6.82)
Controls	Yes	Yes	Yes
Adj. R-squared	15.79%	17.19%	18.57%
#Days	1,608	1,324	1,055
#Obs	116,568	81,222	53,220

Table IA.13 – *REG* and Analyst Recommendation Changes

This table reports results from daily Fama-MacBeth cross-sectional regressions of analyst recommendation changes in the weeks after an earnings announcements on *REG* and other explanatory variables. In columns (1) to (4), the dependent variable is the average recommendation change issued by analysts in the first week after the earnings announcement on day t (i.e., from day $t+1$ to day $t+5$). The dependent variable in columns (5) to (8) is the average recommendation change issued by analysts in the second and third week after day t (i.e., from day $t+6$ to day $t+15$). Firm control variables include *LnSIZE*, *LnBM*, *RET5*, *RET21*, *MOM*, *RVOL*, *ILLIQ*, and *NUMEST*. We report value-weighted time-series averages of the cross-sectional regression estimates based on the daily number of cross-sectional observations. The sample period is from January 1985 to December 2018. t-statistics based on Newey-West standard errors are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	$RecChng_{t+1:t+5}$				$RecChng_{t+6:t+15}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
REG		0.286		-0.334		2.198***		3.132*
		(1.11)		(-0.65)		(2.86)		(1.92)
AFE	-0.053***	-0.058***	-0.040***	-0.044	-0.005	-0.023	0.034	-0.123
	(-4.25)	(-3.66)	(-3.19)	(-1.44)	(-0.10)	(-0.45)	(0.45)	(-1.42)
DGTW			0.008	0.019			0.027	-0.026
			(1.33)	(1.61)			(1.14)	(-0.69)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	3.72%	4.66%	5.33%	5.57%	4.08%	3.94%	9.05%	9.85%
#Days	182	157	157	134	34	22	22	13
#Obs	13,346	13,332	13,332	13,332	7,001	6,996	6,996	6,996

Table IA.14 – Positive and Negative *REG*

This table reports results from daily Fama-MacBeth cross-sectional regressions predicting *AFE* in quarter $q+1$ and monthly Fama-MacBeth cross-sectional regressions predicting *SYY* in month $m+3$. Dummy(*REG*>0) is a dummy variable which equals 1 if *REG* is greater than zero. Dummy(*REG*⩽0) takes the value of one when *REG* is smaller than or equal to zero. The sample period is from January 1985 to December 2018. Columns (1) to (4) show the results for predicting *AFE* in the next quarter. Columns (5) to (7) report the results for predicting *SYY* in the next quarter (i.e., three months ahead). t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	AFE_{q+1}				SYY_{m+3}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
*REG**Dummy(*REG*>0)	3.313***	3.000***	2.980***	2.704***	1.846***	4.234***	3.154***
	(10.45)	(9.67)	(9.21)	(8.20)	(7.03)	(16.30)	(10.77)
*REG**Dummy(*REG*⩽0)	3.068***	2.668***	2.556***	2.184***	0.600**	2.835***	1.873***
	(12.66)	(10.71)	(8.58)	(7.02)	(2.42)	(10.38)	(6.49)
Dummy(*REG*>0)	-0.143**	-0.094	-0.076	0.018	-0.164***	-0.050	-0.095*
	(-2.23)	(-1.50)	(-1.23)	(0.27)	(-3.24)	(-0.98)	(-1.86)
AFE			0.135***	0.133***	0.089***		0.059***
			(13.45)	(12.96)	(15.28)		(9.88)
DGTW			-0.074***	-0.076***		-0.115***	-0.087***
			(-9.80)	(-9.06)		(-14.48)	(-10.82)
SYY				0.016***	0.842***	0.841***	0.841***
				(9.75)	(86.18)	(85.81)	(85.84)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	1.83%	5.37%	9.21%	9.44%	76.35%	76.39%	76.44%
#Days/#Months	3,377	2,677	2,565	2,250	203	203	201
#Obs	202,079	200,030	200,030	172,926	129,589	129,589	129,589

Table IA.15 – Soft Information and the Impact of REG on AFE and SYY

This table reports results from Fama-MacBeth cross-sectional regressions predicting AFE and SYY in quarter $q+1$ (month $m+3$) controlling for "soft" information from earnings conference calls. We construct textual measures based on the management and Q&A transcripts using the Loughran and McDonald dictionary (Loughran and McDonald, 2016), including the difference between the number of positive and negative words scaled by their sum (*Tone*) and the fraction of uncertainty words (*Uncertainty*). Panel A presents results for predicting AFE, and Panel B displays results for predicting SYY, both controlling for management's ($Mgmt$) and analysts' (Ana) tone and uncertainty in earnings conference calls and the full set of firm-level control variables. The sample period is from January 2006 to December 2018, focusing on S&P 500 firms with conference call transcripts. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Predicting AFE

	(1)	(2)	(3)	(4)	(5)	(6)
REG	2.944***	2.912***	2.949***	2.913***	2.982***	2.944***
	(10.14)	(9.79)	(9.83)	(9.71)	(10.00)	(9.62)
$Tone_{Mgmt}$		-0.191		-2.051		-2.512
		(-0.18)		(-1.27)		(-1.03)
$Tone_{Ana}$		-2.68			0.035	-1.799
		(-1.12)			(0.05)	(-0.70)
$Uncertainty_{Mgmt}$			70.208	-34.972		-42.767
			(1.07)	(-0.37)		(-0.33)
$Uncertainty_{Ana}$			-52.855		-21.113	-2.057
			(-1.54)		(-0.91)	(-0.10)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-Squared	9.11%	8.92%	8.75%	8.81%	8.85%	8.55%
#Days	889	856	856	856	856	838
#Obs	74,382	74,382	74,382	74,382	74,382	74,382

Panel B: Predicting SYY

	(1)	(2)	(3)	(4)	(5)	(6)
REG	2.298***	2.275***	2.293***	2.285***	2.276***	2.262***
	(7.09)	(7.09)	(7.17)	(7.19)	(7.09)	(7.14)
$Tone_{Mgmt}$		0.945		0.009		0.562
		(1.23)		(0.02)		(0.73)
$Tone_{Ana}$		5.368			2.452	5.464
		(0.89)			(0.82)	(0.9)
$Uncertainty_{Mgmt}$			76.383	84.236		-53.81
			(0.71)	(0.6)		(-1.37)
$Uncertainty_{Ana}$			33.857**		25.947	28.068
			(2.1)		(1.42)	(1.64)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-Squared	77.67%	77.71%	77.7%	77.7%	77.72%	77.72%
#Months	70	70	70	70	70	70
#Obs	52,686	52,686	52,686	52,686	52,686	52,686

Table IA.16 – The Effect of *REG* on Analyst Earnings Forecast Errors: Controlling for Sales Forecast Errors

This table reports the results from daily Fama-MacBeth cross-sectional regressions of *AFE* in quarters $q+1$ to $q+12$ on *REG* and other explanatory variables (*AFE*, *DGTW*, and *SYY*) in quarter q, with the additional control of analyst sales forecast errors, $SalesForeErr$. $SalesForeErr$ is the difference between the analyst median forecast for sales and the corresponding actual scaled by the firm's market capitalization, recorded in billions. *AFE*, *DGTW*, and *SYY* are analyst forecast errors, earnings announcement day DGTW-adjusted abnormal returns, and firms' Stambaugh et al. (2015) score. Firm control variables include *LnSIZE*, *LnBM*, *RET5*, *RET21*, *MOM*, *RVOL*, *ILLIQ*, *DISP*, and *NUMEST*. The sample period is from January 2002 to December 2018. We report value-weighted time-series averages of the cross-sectional regression estimates based on the daily number of cross-sectional observations. An overview of all variable definitions and descriptions is provided in Internet Appendix Table IA.1. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	(1) AFE_{q+1}	(2) AFE_{q+2}	(3) AFE_{q+3}	(4) AFE_{q+4}	(5) AFE_{q+8}	(6) AFE_{q+12}
REG	2.740***	1.718***	1.595***	1.786***	1.380***	1.042***
	(10.32)	(5.13)	(4.96)	(4.35)	(4.02)	(2.86)
$SalesForeErr$	0.003**	0.002	0.004**	0.003**	0.002*	0.003**
	(2.41)	(1.23)	(2.09)	(2.27)	(1.74)	(2.42)
AFE	0.115***	0.105***	0.077***	0.072***	0.071***	0.071***
	(10.07)	(6.41)	(5.40)	(4.19)	(5.60)	(3.84)
DGTW	-0.057***	-0.031***	-0.031***	-0.042***	-0.020**	-0.012
	(-8.89)	(-3.70)	(-4.55)	(-4.48)	(-2.46)	(-1.26)
SYY	0.020***	0.022***	0.022***	0.020***	0.025***	0.021***
	(9.36)	(6.89)	(9.11)	(8.20)	(6.67)	(7.59)
LnSIZE	-0.115***	-0.111***	-0.119***	-0.123***	-0.143***	-0.177***
	(-4.43)	(-4.37)	(-4.34)	(-3.89)	(-3.69)	(-3.44)
LnBM	0.211***	0.248***	0.206***	0.189***	0.209***	0.149***
	(4.08)	(4.83)	(3.48)	(3.30)	(4.12)	(3.12)
RET5	-0.014*	-0.003	-0.018**	-0.008	0.014	0.000
	(-1.96)	(-0.36)	(-2.17)	(-1.03)	(1.48)	(0.04)
RET21	-0.005	-0.008**	-0.007*	-0.005	-0.004	-0.007
	(-1.24)	(-2.18)	(-1.76)	(-1.10)	(-0.63)	(-1.23)
MOM	-0.005***	-0.005***	-0.002*	-0.001	0.002*	0.001
	(-6.23)	(-4.83)	(-1.75)	(-0.55)	(1.77)	(1.29)
RVOL	0.061	0.264	0.080	0.127	-0.657**	-0.646**
	(0.32)	(1.11)	(0.31)	(0.44)	(-2.12)	(-2.31)
ILLIQ	3.029*	1.638	6.947**	4.599*	3.61	-4.091
	(1.94)	(0.94)	(2.10)	(1.91)	(0.68)	(-1.02)
DISP	36.581***	17.707***	25.436***	29.506***	30.588***	50.201***
	(4.43)	(2.85)	(3.07)	(4.10)	(3.62)	(4.53)
NUMEST	-0.072	-0.125**	-0.088	-0.08	-0.093	-0.083
	(-1.21)	(-1.97)	(-1.47)	(-0.96)	(-1.21)	(-1.03)
Adj. R-Squared	9.02%	7.45%	6.59%	6.25%	5.25%	4.4%
#Days	1,071	1,063	1,061	1,054	1,030	924
#Obs	88,996	87,371	85,848	84,491	79,109	68,728

Table IA.17 – REG and SYY Composite Mispricing Scores: Controlling for Sales Forecast Errors

This table reports results from monthly Fama-MacBeth cross-sectional regressions of firms' SYY scores in months $m+3$ to $m+36$ on REG and other explanatory variables (AFE, $DGTW$, and SYY) in month m, with the additional control of analyst sales forecast errors, $SalesForeErr$. $SalesForeErr$ is the difference between the analyst median forecast for sales and the corresponding actual scaled by the firm's market capitalization, recorded in billions. Firm control variables include *LnSIZE*, *LnBM*, *MRET*, *MMOM*, *MRVOL*, and *MILLIQ*. All variables except for *REG*, *AFE*, and $DGTW$ are observed at the end of the month of the earnings announcement. The sample period is from January 2002 to December 2018. We report value-weighted time-series averages of the cross-sectional regression estimates based on the number of cross-sectional observations. An overview of all variable definitions and descriptions is provided in Internet Appendix Table IA.1. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	SYY_{m+3}	SYY_{m+6}	SYY_{m+9}	SYY_{m+12}	SYY_{m+24}	SYY_{m+36}
REG	2.337***	2.9***	3.324***	3.229***	2.913***	2.935***
	(6.8)	(8.42)	(10.57)	(7.61)	(5.07)	(4.97)
$SalesForeErr$	-0.003***	-0.004***	-0.008***	-0.010***	0.001	-0.001*
	(-2.85)	(-3.06)	(-3.80)	(-2.80)	(0.35)	(-1.91)
AFE	0.067***	0.031***	0.042***	0.047**	0.039***	0.022
	(7.28)	(2.85)	(2.73)	(2.08)	(2.88)	(0.98)
$DGTW$	-0.059***	-0.049***	-0.044***	-0.033*	-0.024***	-0.040***
	(-6.20)	(-3.77)	(-3.43)	(-1.90)	(-2.70)	(-3.83)
SYY	0.847***	0.776***	0.676***	0.583***	0.502***	0.460***
	(59.52)	(63.48)	(65.63)	(71.24)	(44.60)	(73.94)
LnSIZE	-0.238***	-0.38***	-0.581***	-0.803***	-1.121***	-1.130***
	(-4.25)	(-4.35)	(-4.65)	(-5.54)	(-4.53)	(-4.30)
LnBM	-0.162***	-0.128	-0.067	0.143	0.608***	0.765***
	(-2.76)	(-1.42)	(-0.67)	(1.51)	(3.73)	(4.58)
MRET	-0.126***	-0.123***	-0.110***	-0.103***	0.031***	0.009
	(-22.15)	(-16.28)	(-12.69)	(-11.28)	(3.96)	(0.74)
MMOM	0.006***	0.035***	0.066***	0.090***	0.086***	0.069***
	(3.30)	(12.58)	(17.17)	(18.27)	(12.33)	(11.19)
MRVOL	1.785	2.896	3.291	3.562	-9.022***	-10.998***
	(1.00)	(1.09)	(0.97)	(1.14)	(-4.26)	(-2.93)
MILLIQ	-1.081**	-1.149	-2.084	-2.887**	-3.03*	-0.859
	(-2.28)	(-1.55)	(-1.65)	(-2.08)	(-1.86)	(-1.05)
Adj. R-Squared	77.41%	64.23%	49.67%	38.77%	30.54%	26.59%
#Months	83	83	81	78	72	66
#Obs	61,414	59,076	56,890	54,381	47,109	40,087

Table IA.18 – Individual Anomaly Returns Conditioning on *REG*

This table reports the cumulative monthly *DGTW* abnormal returns (expressed in percent) of portfolios formed based on the quintile ranking of characteristics related to individual anomalies at the end of month $m-1$ and the sign of *REG* in month m. The table extends the analysis from Table 7 to individual anomalies and presents the cumulative returns for two long-short portfolios formed based on individual anomaly scores and *REG*. The "REG Against" and "REG With" portfolios are constructed as in Table 7, where we replace the composite ranking with the individual anomaly ranking. Panels (a), (b), and (c) display the corresponding portfolio returns for the Composite Equity Issues, Investment to Assets, and Gross Profitability anomalies, respectively. The sample period is from January 1985 to December 2018. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Anomaly – Composite Equity Issues

	$MDGTW_m$	$MDGTW_{m:m+1}$	$MDGTW_{m:m+3}$	$MDGTW_{m:m+6}$	$MDGTW_{m:m+12}$	$MDGTW_{m:m+24}$	$MDGTW_{m:m+36}$
REG Against	3.70***	3.43***	2.39***	1.01	-0.75	-0.47	-1.81
	(14.65)	(11.36)	(4.40)	(1.13)	(-0.53)	(-0.23)	(-0.75)
REG With	-4.81***	-4.91***	-5.60***	-6.18***	-6.27***	-5.46**	-4.94
	(-16.57)	(-13.97)	(-8.97)	(-6.17)	(-3.35)	(-2.02)	(-1.33)
		$MDGTW_{m+1}$	$MDGTW_{m+1:m+3}$	$MDGTW_{m+1:m+6}$	$MDGTW_{m+1:m+12}$	$MDGTW_{m+1:m+24}$	$MDGTW_{m+1:m+36}$
REG Against		-0.24	-1.28***	-2.56***	-4.21***	-3.84*	-5.32**
		(-1.44)	(-3.33)	(-3.19)	(-3.18)	(-1.92)	(-2.11)
REG With		-0.11	-0.74**	-1.30**	-1.48	-0.61	-0.04
		(-0.61)	(-1.97)	(-2.01)	(-1.13)	(-0.30)	(-0.01)

Panel B: Anomaly – Investment to Assets

	$MDGTW_m$	$MDGTW_{m:m+1}$	$MDGTW_{m:m+3}$	$MDGTW_{m:m+6}$	$MDGTW_{m:m+12}$	$MDGTW_{m:m+24}$	$MDGTW_{m:m+36}$
REG Against	3.70***	3.59***	3.05***	2.12***	1.28	-1.40	-2.79
	(16.09)	(12.81)	(7.23)	(3.23)	(1.07)	(-0.74)	(-1.19)
REG With	-4.67***	-4.66***	-4.97***	-5.28***	-5.95***	-7.12***	-7.37***
	(-19.75)	(-17.84)	(-12.07)	(-9.09)	(-6.41)	(-4.05)	(-4.09)
		$MDGTW_{m+1}$	$MDGTW_{m+1:m+3}$	$MDGTW_{m+1:m+6}$	$MDGTW_{m+1:m+12}$	$MDGTW_{m+1:m+24}$	$MDGTW_{m+1:m+36}$
REG Against		-0.10	-0.66**	-1.46***	-2.37**	-4.87***	-6.34***
		(-0.71)	(-2.30)	(-2.93)	(-2.33)	(-3.07)	(-3.27)
REG With		0.12	-0.16	-0.43	-1.19	-2.36	-2.29
		(0.75)	(-0.50)	(-0.80)	(-1.34)	(-1.3)	(-1.17)

Panel C: Anomaly – Gross Profitability

	$MDGTW_m$	$MDGTW_{m:m+1}$	$MDGTW_{m:m+3}$	$MDGTW_{m:m+6}$	$MDGTW_{m:m+12}$	$MDGTW_{m:m+24}$	$MDGTW_{m:m+36}$
REG Against	3.60***	2.96***	2.12***	0.60	-0.99	-2.98	-5.02**
	(11.38)	(7.39)	(3.58)	(0.67)	(-0.72)	(-1.21)	(-2.01)
REG With	-5.31***	-6.20***	-6.43***	-6.85***	-7.76***	-8.93***	-7.35**
	(-18.42)	(-17.13)	(-10.05)	(-6.78)	(-5.19)	(-3.51)	(-2.15)
		$MDGTW_{m+1}$	$MDGTW_{m+1:m+3}$	$MDGTW_{m+1:m+6}$	$MDGTW_{m+1:m+12}$	$MDGTW_{m+1:m+24}$	$MDGTW_{m+1:m+36}$
REG Against		-0.75***	-1.57***	-3.04***	-4.59***	-6.27***	-7.98***
		(-3.03)	(-3.51)	(-4.01)	(-3.86)	(-2.59)	(-3.07)
REG With		-0.87***	-1.21**	-1.62*	-2.75**	-3.85*	-2.09
		(-3.69)	(-2.45)	(-1.93)	(-2.06)	(-1.66)	(-0.65)

Table IA.19 – Anomaly Returns Conditioning on $DGTW$

This table repeats the analysis conducted in Table 7, where REG is replaced with DGTW. In particular, the table reports the cumulative monthly $DGTW$ abnormal returns (expressed in percent) of portfolios formed based on the quintile ranking of SYY (an overvaluation score) at the end of month $m-1$ and the sign of the earnings-announcement-day abnormal return, $DGTW$, in month m. Portfolio returns are presented for different horizons from month m (including the earning announcement month) to $m+n$ ($n = 1, 3, 6, 12, 24, 36$) and from month $m+1$ (excluding the earning announcement month) to $m+n$ ($n = 3, 6, 12, 24, 36$). Panel A reports abnormal returns of four portfolios formed on SYY being in the top (bottom) quintile and the $DGTW$ realization being positive (negative). In Panel B, the portfolio "$DGTW$ Against" represents a long-short portfolio that takes a long position in stocks with SYY scores being in the top quintile (indicating overvaluation) in month $m-1$ and a positive $DGTW$ on the announcement day in month m, and a short position in stocks with SYY scores being in the bottom quintile (indicating undervaluation) in month $m-1$ and a negative realization of $DGTW$. The portfolio "$DGTW$ With" represents a long-short portfolio that takes a long position in stocks with SYY being in the top quintile in month $m-1$ and a negative realization of $DGTW$, and a short position in stocks with SYY scores being in the bottom quintile in month $m-1$ and a positive realization of $DGTW$. The sample period is from January 1985 to December 2018. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Portfolios Based on SYY *and* DGTW

	$MDGTW_m$	$MDGTW_{m:m+1}$	$MDGTW_{m:m+3}$	$MDGTW_{m:m+6}$	$MDGTW_{m:m+12}$	$MDGTW_{m:m+24}$	$MDGTW_{m:m+36}$
SYY Q5 & $DGTW > 0$	3.96***	4.10***	3.17***	2.10***	1.34**	1.05	2.09*
	(21.17)	(18.02)	(9.3)	(3.99)	(2.01)	(1.11)	(1.67)
SYY Q5 & $DGTW < 0$	-3.78***	-4.04***	-4.79***	-5.84***	-6.93***	-6.87***	-5.69***
	(-21.94)	(-18.35)	(-16.15)	(-12.55)	(-10.31)	(-7.27)	(-3.51)
SYY Q1 & $DGTW > 0$	3.92***	4.43***	4.98***	5.31***	5.89***	7.26***	9.19***
	(35.13)	(34.13)	(25.32)	(17.77)	(11.17)	(7.37)	(7.5)
SYY Q1 & $DGTW < 0$	-3.26***	-3.13***	-3.07***	-2.87***	-2.65***	-1.42**	-0.75
	(-24.55)	(-21.2)	(-14.98)	(-9.17)	(-5.43)	(-2.18)	(-0.8)

Panel B: Portfolios Based on DGTW *Being Against or With the* SYY *Correction Path*

	$MDGTW_m$	$MDGTW_{m:m+1}$	$MDGTW_{m:m+3}$	$MDGTW_{m:m+6}$	$MDGTW_{m:m+12}$	$MDGTW_{m:m+24}$	$MDGTW_{m:m+36}$
$DGTW$ Against	7.18***	7.20***	6.21***	4.94***	3.87***	2.40*	2.85
	(28.5)	(23.84)	(13.71)	(7.48)	(4.49)	(1.93)	(1.53)
$DGTW$ With	-7.68***	-8.43***	-9.76***	-11.11***	-0.12.72***	-14.03***	-14.89***
	(-32.91)	(-29.04)	(-24.76)	(-18.13)	(-13.35)	(-11.38)	(-6.58)
$DGTW$ Against - $DGTW$ With	14.86***	15.63***	15.97***	16.05***	16.59***	16.43***	17.74***
	(43.27)	(37.31)	(26.60)	(17.81)	(12.91)	(9.38)	(6.05)

	$MDGTW_{m+1}$	$MDGTW_{m+1:m+3}$	$MDGTW_{m+1:m+6}$	$MDGTW_{m+1:m+12}$	$MDGTW_{m+1:m+24}$	$MDGTW_{m+1:m+36}$
$DGTW$ Against	-0.05	-1.02***	-2.20***	-3.23***	-4.65***	-4.18**
	(-0.34)	(-3.34)	(-4.48)	(-4.53)	(-3.86)	(-1.97)
$DGTW$ With	-0.75***	-2.01***	-3.37***	-5.09***	-6.27***	-7.00***
	(-4.19)	(-6.12)	(-6.32)	(-5.66)	(-5.53)	(-3.52)
$DGTW$ Against - $DGTW$ With	0.70***	0.99**	1.17	1.86	1.62	2.82
	(3.02)	(2.21)	(1.61)	(1.62)	(0.98)	(0.97)

Table IA.20 – Anomaly Returns Conditioning on SUE

This table repeats the analysis conducted in Table 7, where REG is replaced with SUE. In particular, the table reports the cumulative monthly $DGTW$ abnormal returns (expressed in percent) of portfolios formed based on the quintile ranking of SYY (an overvaluation score) at the end of month $m-1$ and the sign of the earnings surprise, SUE, in month m. Portfolio returns are presented for different horizons from month m (including the earning announcement month) to $m+n$ ($n = 1, 3, 6, 12, 24, 36$) and from month $m+1$ (excluding the earning announcement month) to $m+n$ ($n = 3, 6, 12, 24, 36$). Panel A reports abnormal returns of four portfolios formed on SYY being in the top (bottom) quintile and the SUE realization being positive (negative). In Panel B, the portfolio "SUE With" represents a long-short portfolio that takes a long position in stocks with SYY scores being in the top quintile (indicating overvaluation) in month $m-1$ and a positive SUE on the announcement day in month m, and a short position in stocks with SYY scores being in the bottom quintile (indicating undervaluation) in month $m-1$ and a negative SUE. The portfolio "SUE Against" represents a long-short portfolio that takes a long position in stocks with SYY scores being in the top quintile in month $m-1$ and a negative SUE, and a short position in stocks with SYY scores being in the bottom quintile in month $m-1$ and a positive SUE. The sample period is from January 1985 to December 2018. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Portfolios Based on SYY *and* SUE

	$MDGTW_m$	$MDGTW_{m:m+1}$	$MDGTW_{m:m+3}$	$MDGTW_{m:m+6}$	$MDGTW_{m:m+12}$	$MDGTW_{m:m+24}$	$MDGTW_{m:m+36}$
SYY Q5 & $SUE>0$	2.88***	3.04***	2.58***	1.63***	1.16*	1.46	2.14
	(14.83)	(12.4)	(7.38)	(3.23)	(1.79)	(1.44)	(1.26)
SYY Q5 & $SUE<0$	-3.16***	-3.51***	-4.78***	-6.06***	-7.30***	-7.26***	-6.34***
	(-18.3)	(-15.56)	(-13.33)	(-11.48)	(-8.89)	(-5.13)	(-3.49)
SYY Q1 & $SUE>0$	2.33***	2.77***	3.29***	3.64***	4.36***	5.77***	7.20***
	(24.73)	(23.16)	(17.81)	(10.33)	(7.89)	(6.37)	(6.05)
SYY Q1 & $SUE<0$	-3.33***	-3.30***	-3.48***	-3.34***	-3.49***	-3.28***	-2.50**
	(-24.46)	(-19.67)	(-14.76)	(-11.2)	(-6.93)	(-3.6)	(-2.41)

Panel B: Portfolios Based on SUE *Being Against or With the* SYY *Correction Path*

	$MDGTW_m$	$MDGTW_{m:m+1}$	$MDGTW_{m:m+3}$	$MDGTW_{m:m+6}$	$MDGTW_{m:m+12}$	$MDGTW_{m:m+24}$	$MDGTW_{m:m+36}$
SUE With	6.47***	6.59***	6.37***	5.36***	5.14***	5.23***	5.24**
	(27.62)	(20.98)	(15.13)	(9.68)	(6.53)	(3.92)	(2.23)
SUE Against	-5.57***	-6.33***	-8.02***	-9.58***	-11.41***	-12.69***	-13.31***
	(-28.66)	(-23.74)	(-17.72)	(-13.48)	(-11.19)	(-8.32)	(-6.93)
SUE With - SUE Against	12.04***	12.92***	14.39***	14.94***	16.55***	17.92***	18.55***
	(39.56)	(31.36)	(23.28)	(16.58)	(12.85)	(8.84)	(6.11)

	$MDGTW_{m+1}$	$MDGTW_{m+1:m+3}$	$MDGTW_{m+1:m+6}$	$MDGTW_{m+1:m+12}$	$MDGTW_{m+1:m+24}$	$MDGTW_{m+1:m+36}$
SUE With	0.02	-0.24	-1.27**	-1.54*	-1.44	-1.42
	(0.12)	(-0.68)	(-2.56)	(-1.92)	(-1.03)	(-0.54)
SUE Against	-0.76***	-2.38***	-3.94***	-5.77***	-6.79***	-7.16***
	(-4.15)	(-5.87)	(-5.97)	(-5.69)	(-4.22)	(-3.62)
SUE With - SUE Against	0.78***	2.14***	2.67***	4.23***	5.35***	5.74*
	(3.15)	(3.98)	(3.23)	(3.27)	(2.51)	(1.74)

Table IA.21 – The Effect of REG on AFE: Global Settlement Event

This table reports the results from difference-in-differences regressions of AFE in quarter $q+1$ on REG and other explanatory variables in quarter q. We analyze the impact of the Global Settlement (GS) in the year 2002 and define the three years before the event (1999, 2000, and 2001) as the pre-event period and the three years after the event (2003, 2004, and 2005) as the post-event period. Specifically, we generate two dummy variables PRE and $POST$ to indicate if an observation is before or after the event. In addition, we classify firms into "GS" and "NonGS" firms: "GS" firms are those that are consistently ranked above the cross-sectional median during PRE and POST periods in terms of the percentage of analysts affected by the Global Settlement, and "NonGS" firms are those that are consistently ranked below the cross-sectional median during PRE and POST periods in terms of the percentage of analysts affected by the Global Settlement. GS and $NonGS$ are two dummy variables that indicate whether a firm is a "GS" firm or a "NonGS" firm as defined above. We include the full set of control variables. An overview of all variable definitions and descriptions is provided in Internet Appendix Table IA.1. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	AFE_{q+1}		
	Baseline (1)	Sub-Groups (2)	Interaction (3)
$REG \times POST \times GS$		4.374***	4.100*
		(2.85)	(1.65)
$REG \times POST \times NonGS$		0.692	
		(0.58)	
$REG \times PRE \times GS$		2.546**	
		(2.23)	
$REG \times PRE \times NonGS$		2.964*	
		(1.73)	
$REG \times GS$			-0.418
			(-0.23)
$REG \times POST$			-2.272
			(-1.42)
REG	2.272**		2.964*
	(2.30)		(1.73)
Controls	Yes	Yes	Yes
Adj. R-Squared	6.11%	6.17%	6.17%
#Obs	5,338	5,338	5,338

Table IA.22 – The Effect of REG on SYY: Additional Firm Characteristics

This table reports the coefficients on REG from Fama-MacBeth cross-sectional regressions of SYY in months m+3 to m+36 on REG and other explanatory variables in month m. The difference of the coefficients on REG between different subsamples and the corresponding t-statistics are also reported. We split our sample in two subsamples each based on the cross-sectional monthly medians of: (i) analyst coverage, (ii) firm market cap, (iii) institutional ownership, and (iv) analyst disagreement. All dependent variables except for REG, AFE, and $DGTW$ are observed at the end of the month of earnings announcement day t. Firm control variables include *LnSIZE*, *LnBM*, *MRET*, *MMOM*, *MRVOL*, and *MILLIQ*. The sample period is from January 1985 to December 2018. We report value-weighted time-series averages of the cross-sectional regression estimates based on the daily number of cross-sectional observations. t-statistics are reported below the coefficient estimates in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	(1) SYY_{m+3}	(2) SYY_{m+6}	(3) SYY_{m+9}	(4) SYY_{m+12}	(5) SYY_{m+24}	(6) SYY_{m+36}
			Analyst Coverage			
Low Coverage	2.594***	3.198***	3.252***	2.998***	0.509	-0.091
	(9.96)	(9.60)	(8.42)	(7.59)	(1.01)	(-0.17)
High Coverage	1.769***	2.409***	2.538***	2.356***	1.413***	1.093**
	(6.98)	(7.24)	(6.47)	(5.87)	(2.88)	(2.40)
Low - High	0.825**	0.789*	0.714	0.642	-0.904	-1.184*
	(2.27)	(1.68)	(1.30)	(1.14)	(-1.29)	(-1.68)
			Firm Market Cap			
Small	2.680***	3.437***	3.508***	3.022***	0.494	-0.068
	(9.89)	(9.76)	(8.33)	(6.80)	(1.02)	(-0.14)
Large	2.092***	2.705***	2.758***	2.579***	1.425***	1.048**
	(7.74)	(8.02)	(7.12)	(6.06)	(3.01)	(2.15)
Small - Large	0.651**	0.732	0.750	0.443	-0.931	-1.116
	(1.73)	(1.50)	(1.31)	(0.72)	(-1.37)	(-0.23)
			Institutional Ownership			
Low IO	2.509***	3.279***	3.332***	3.160***	1.096**	0.812
	(10.30)	(10.38)	(8.65)	(7.78)	(2.30)	(1.53)
High IO	1.972***	2.461***	2.503***	2.110***	0.922**	0.251
	(7.43)	(7.31)	(6.48)	(5.21)	(1.98)	(0.56)
Low - High	0.537	0.818*	0.829	1.050*	0.174	0.561
	(1.49)	(1.77)	(1.52)	(1.83)	(0.26)	(0.81)
			Analyst Disagreement			
High DIS	2.784***	3.34***	3.204***	2.824***	0.501	-0.558
	(9.73)	(8.71)	(6.83)	(5.72)	(0.92)	(-1.08)
Low DIS	1.365***	2.090***	2.154***	1.723***	0.872*	0.732*
	(5.84)	(6.99)	(5.89)	(4.28)	(1.83)	(1.70)
High - Low	1.419***	1.250**	1.050*	1.101*	-0.371	-1.290*
	(3.84)	(2.57)	(1.77)	(1.73)	(-0.51)	(-1.92)