Investor (Mis)reaction, Biased Beliefs, and the Mispricing Cycle*

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Abstract

We construct a new measure that captures market reaction to earnings information ("*REG*"). High *REG* scores positively predict analyst forecast errors and firm mispricing (overvaluation) scores, especially for build-up anomalies. Analyst forecast errors are slower to converge when *REG* provides confirming information. In turn, *REG* is positively predicted by analyst forecasts errors and higher mispricing, leading to a continuation of firm overvaluation over a few quarters. Overall, our results reveal how the market's (mis)reaction feeds back into the belief formation of analysts, which partially explains the slow correction of firm mispricing.

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

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1. Introduction

The traditional view of financial markets states that the market aggregates dispersed information efficiently and incorporates new information correctly (Hayek, 1945; Grossman, 1976; Holthausen and Verrecchia, 1988). Recent research, however, recognizes that investors' expectations can be biased,[1] leading to under- or overreaction to information.[2] Biases in investors' expectations also take an important part in the longstanding debate on risk vs. mispricing (e.g., Kozak et al., 2018) and are relevant for explaining anomaly returns. In particular, recent evidence indicates that analyst forecasts are systematically over-optimistic (pessimistic) for anomaly short (long) positions (La Porta, 1996; La Porta et al., 1997; Engelberg et al., 2018; Bordalo et al., 2019; Engelberg et al., 2020).

While analyst errors line up inversely with anomaly returns, a natural question to ask is why such biases and observed mispricing persist over a long time. Specifically, why are analysts' biased expectations not corrected by the response of other market participants? Alternatively, can analysts be influenced by the market response in a way that amplifies the formation of their biased beliefs? While a plethora of studies explore the existence of a bias and link it to overall mispricing, there is still little *direct* empirical evidence on the interplay between the expectations formation of subgroups of investors and how it contributes to the correction or amplifications of such biases.

A key challenge towards answering these questions is, however, the difficulty of quantifying

[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), confirmation bias (Nickerson, 1998; Pouget et al., 2017; Cookson et al., 2021; Hirshleifer et al., 2021), sticky belief dynamics (Bordalo et al., 2019), and catch-all sentiment (De Long et al., 1990; Baker and Wurgler, 2006)

[2]Examples include overreaction at the market level (Greenwood and Shleifer, 2014; Cassella and Gulen, 2018), overreaction in the cross-section of stocks (Bordalo et al., 2019; Da et al., 2021), and underreaction to analysts forecasts and earnings information (e.g., Bernard and Thomas, 1989, 1990; Chan et al., 1996; Cready and Gurun, 2010; Hartzmark and Shue, 2018).

the extent of market biases relative to the available fundamental information at a given point in time. To do so, we take a non-parametric approach and measure market participants' reaction to earnings information on earnings announcements days. Specifically, we compare the ranking of the return response (i.e., market participants' beliefs) to the ranking of unexpected earnings (i.e., the fundamental information).[3] We call this measure the *R*eturn *E*arnings *G*ap (*REG*). Specifically, a higher (lower) *REG* would be an indication of a higher (lower) response by market participants for a given quantity of earnings information.

Using this measure, we provide new empirical evidence on the dynamic interaction between two prominent groups of investors: analysts, professional investors who provide valuable information to market participants, and market participants who trade and reflect their beliefs into stock prices. Ex-ante, if market participants share the same systematic bias expressed in analysts' forecasts, a higher (lower) *REG* could reflect a similar excessive optimism (pessimism) toward the firm prospects. On the other hand, *REG* could reflect a rational reaction to "soft" information released together with the earnings announcement. Empirically, we find support in favor of the former. That is, market participates make systematic mistakes, which builds up into overall mispricing. Specifically, we show that the market's initial response to earnings announcements feeds back into analysts' expectations in a way that increases their earnings forecast errors in the same direction over the subsequent quarters, leading to persistently biased expectations and a build-up in mispricing that takes several quarters to correct. This dynamics can be seen in Figure 1, which plots the mispricing cycle, given the initial market reaction, over the subsequent 12 quarters. We also find that analysts' biased expectations

[3]The market response and *SUE* need to be scaled to allow for a fair comparison across stocks and over time. We follow Daniel et al. (1997) and use the characteristic-based adjustment approach to adjust the market response. We follow Mendenhall (2004) and Livnat and Mendenhall (2006) and use I/B/E/S to construct *SUE* as the difference between the actual and the most recent analyst earnings forecast consensus normalized by the dispersion of the consensus, accounting for stock characteristics and time fixed effects.

and firm mispricing conditions feed back into market participants' reaction, pointing to a dynamic amplification effect. Overall, using our *REG* measure, we are able to identify new mispricing build-up dynamics that were not explored in previous research.

By the nature of the measure, the return on day t is high (low) for a positive (negative) *REG*. Day t return response is only followed by a small reversal suggesting that the effect is permanent, reflecting investors' beliefs about the firm. Supporting this argument we find that institutional investors persistently trade in the same direction of *REG* on day t and the subsequent five trading days, where the small reversal is consistent with a liquidity shock (Da et al., 2014).

If analysts fail to disentangle the noise from information contained in the market response, market participants' (mis)reaction can result in a positive increase in *AFE*. For example, a positive market response to the negative earnings surprise can reinforce analysts' errors since analysts may view this response as a validation (confirmation) of their expectations (Pouget et al., 2017). We find that *REG* positively predicts analyst forecast errors over subsequent quarters. This suggests that market participants' reaction feeds back into analyst forecast errors in a way that distorts their expectation formation. To capture overall firm mispricing conditions, we include Stambaugh et al. (2012) mispricing score (*MISP*). We confirm that *MISP* also has a positive effect on *AFE*. More importantly, contrasting the effect of *REG* with *MISP*, we find that the effect of *REG* is twice as large, revealing the importance of *REG*.

Consistent with *REG* capturing biased beliefs, we find a positive predictive relation between *REG* and *MISP* over the subsequent quarters. While *AFE* also positively predicts *MISP*, the economic significance of *REG* is three times larger than that of *AFE*. In addition, the effect of *REG* on mispricing reaches its peak after four quarters, while the effect of *AFE* decays after the first quarter. This shows that *REG* is able to capture a gradual mispricing build-up due to the initial misreaction, where the mispricing effect is then reversed in years 2 and 3.

To better understand the effect of *REG* on firm mispricing we focus on two additional sets of anomaly classifications. The first decomposes *MISP* into the *PERF* and *MGMT* anomaly groups as suggested by Stambaugh and Yuan (2017). The second takes advantage of van Binsbergen et al. (2021)'s *Build-Up* and *Resolution* anomaly classification.[4] While both *MGMT* and *PERF* are positively affected by *REG*, the mispricing cycle of the *MGMT* anomaly group takes longer to reach its peak. This is consistent with the longer(shorter) nature of *MGMT*(*PERF*). Even more interesting is the stark difference between the *Build-Up* and *Resolution* anomalies. Consistent with van Binsbergen et al. (2021) mispricing metrics, we find that the mispricing cycle — that is, the deviation from the true value — appears in the set of the *Build-Up* anomalies. In particular, it takes up to 2 years to reach the peak. In contrast, by the nature of the resolution anomalies, *REG* captures the peak of the mispricing where afterward a convergence toward fundamental values is observed. The overall anomaly findings extend the view in current studies, such as Engelberg et al. (2018), who show that new information arrival attenuates existing mispricing. While previous research identifies the correction phase of mispricing, *REG* is able to capture the build-up in analyst expectations and mispricing, where at some point as "contradicting" information arrives, investors recognize the overreaction and anomalies earn their returns.

[4]Stambaugh and Yuan (2017) classify the set of 11 anomalies into two clusters, "PERF" and "MGMT". Based on the grouping *MGMT* captures anomalies that can be triggered by management actions (*MGMT*), such as net stock issuance, accruals, and asset growth, and can be viewed as capturing longer-term mispricing effects. *PERF* is more driven by performance, such as momentum, ROA, and distress, and can be viewed as capturing shorter-term mispricing effects (Birru et al., 2020). Second, a recent work by van Binsbergen et al. (2021) shows that anomalies can be classified as "build-up" or "resolution" anomalies. Importantly, build-up anomalies capture the creation of mispricing, while resolution anomalies capture the correction of mispricing.

After establishing the effect of *REG* on *AFE* and a wide range set of anomalies, a natural question to ask is, "what explains *REG*?" We find that *REG* is positively predicted by *AFE* and *MISP*. This suggests a dynamic amplification effect where *REG* leads to higher *AFE* and *MISP*, which in turn leads to higher *REG*. This result is consistent with previous research that finds that investors often fail to fully factor these biases into market prices in a timely fashion (e.g., Hughes et al., 2008; Frankel and Lee, 1998; So, 2013). Interestingly, we also find that past month returns and the earnings announcement day return negatively predict *REG*. This is consistent with the correction phase documented in Engelberg et al. (2018), and further highlights the difference between "raw" returns and the relative ranking captured by *REG*. Finally, the positive lead-lag relation between *REG* and *AFE* points to an amplification effect between these two groups of investors, provides some explanation for why these effects take more than a few quarters to converge.

The behavioral literature suggests a host of explanations for the existence of such biases. One explanation is "confirmation bias" (Pouget et al., 2017; Cookson et al., 2021; Hirshleifer et al., 2021), where analysts interpret the market response as a confirmation of their initial expectations. Another explanation can include extrapolative or diagnostic expectations (Bordalo et al., 2019), where analysts put more weight on the market's relative overreaction response signal. Separating between the potential behavioral explanations is not the main focus of our study, and is not trivial. But, we provide evidence that is consistent with the confirmation channel. Specifically, we look at cases where *AFE* and *REG* are both positive or both negative (that is, *REG* "confirms" *AFE*) and cases where the two are in the opposite direction. We show that analysts' biased expectations are slower to converge when both signals are in the same direction.

Besides analyst earnings forecasts, we also look at analysts' price targets and recommendation changes (Brav and Lehavy, 2003; Jegadeesh et al., 2004; Da and Schaumburg, 2011; Engelberg et al., 2020). We find consistent results with our main findings. Using analysts' 12-month price target estimates, we find that the 12-month implied error (measured as the difference between the forecasted and actual 12-month returns) is positively predicted by *REG*. Similarly, we find that analysts' recommendations changes tend to be more positive.

Our paper first contributes to the broad literature on risk, mispricing, and anomaly returns. Previous literature has linked analysts' biases with anomaly returns. The literature also showed that information arrival pushes anomaly returns in the right direction, consistent with the correction of biased expectations. We add to the literature by exploring the interaction between market participants' and analysts' expectations. We show that analysts' and market participants' biased expectations positively predict each other, pointing to an amplification effect. Putting our findings on a timeline relative to previous findings, we are able to identify an early build-up phase of firm mispricing, where at some point, information arrival pushes mispricing in the right direction.

Second, our paper contributes to the literature on investor beliefs, in particular on how agents form their expectations and process the arrival of fundamental news. The literature mostly considered how analysts revise their forecasts to earnings information. Our paper shows that, in addition, analysts also take into account how the market reacts to the arrival of new information. Specifically, we show that analysts fail to disentangle the noise from information, leading to larger biases. Consistent with that, we provide evidence consistent with analysts consuming biased confirmatory information. Related, the market participants' reaction accompanied by institutional trading is consistent with Edelen et al. (2016) who find that institutional investors trade in the wrong direction of anomaly returns.

Third, another strand of literature investigates the drivers of market reaction to earnings announcements. For example, Mian and Sankaraguruswamy (2012) show that a positive sentiment leads to a more positive market response. Hartzmark and Shue (2018) find that today's reaction to earnings surprises is weaker if past earnings surprise was very positive, in line with a "contrast effect". Our approach allows us to identify in a systematic way misrecations to earnings information in the cross-section of stocks and link them to analysts' forecast errors and firm mispricing conditions.

2. Measures Construction and Data

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

Earnings announcements are one of the most important sources of firm-specific information, where firms convey valuable cash flow information to market participants. Investors, in turn, reflect their aggregate valuation into stock prices.

While the relation between earnings announcements and stock returns was extensively explored in previous studies, we propose a new measure that is designed to capture the *relative* market reaction to firm earnings information. Specifically, we use a non-parametric approach to measure the relative rankings of adjusted standardized earnings surprise ($AdjSUE$) and characteristic-adjusted abnormal return ($DGTW$) of each earnings announcement. This allows us to capture the extent to which the stock price response to the cash flow information deviates from the average response. A positive (negative) number indicates that the market reaction is higher(lower) than one would expect, on average.

We first construct the adjusted standardized earnings surprise component ($AdjSUE$). For each earnings announcement, we obtain the actual EPS, the median of analysts' EPS forecasts, and the standard deviation of their EPS forecasts. Following Mendenhall (2004), we estimate the standardized unexpected earnings, SUE as follows:

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

where $EPS_{i,t}^{Actual}$ is the firm actual EPS reported on the earnings announcement day, where after market close announcements are shifted to the next trading day. Med($EPS_{i.t}^{Estimate}$) and SD($EPS_{i.t}^{Estimate}$) are the last available median and the standard deviation of analysts' EPS forecast consensus 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 splits using the cumulative adjustment factor 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 of different days or 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 the day-of-week and month-of-year dummies which control for periodical variations in unexpected earnings. The regression residual $\epsilon_{i,t}$ is our $AdjSUE_{i,t}$ component for each stock i and earnings day t. Finally, to prevent a look-ahead bias, for each earnings day t we use information from a one-year backward rolling window up to day t.

Next, to construct the second component of our REG measure (the stock price adjustment), we compute the daily characteristic-adjusted abnormal returns following the approach of Daniel et al. (1997) (hereafter, DGTW), 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 in hand, we turn to construct our REG measures. For each earnings announcement of firm i on day t, we independently sort all earnings announcements over the past year (including day t) by their $DGTW$ and $AdjSUE$ components into 1,000 bins. We denote the relative rankings of its $DGTW_{i,t}$ and $AdjSUE_{i,t}$ as $Rank_{i,t}^{DGTW}$ and $Rank_{i,t}^{AdjSUE}$, respectively. We then define REG as follows:

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

where for ease of interpretation, we scale the difference in relative rankings between $DGTW$ and $AdjSUE$ by the number of bins minus one. This makes the REG measure range from -0.5 to 0.5. Thus, one unit change in the REG from -0.5 to 0.5 is implying the flip from the most positive market reaction to the most negative market reaction.

The value of $REG_{i,t}$ is determined based on available information up to day t. Specifically, we use a ranking procedure based on a one-year rolling window that expands backward from day t (inclusive). Besides preventing a look-ahead bias, the use of one-year information allows us to take into account time-varying changes that can affect the relative ranking.[5] Finally, in Appendix A.1 we show that constructing REG based on the relative rankings of 1) unadjusted earnings surprise ($SUE_{i,t}$) and raw returns ($RET_{i,t}$), or 2) adjusted earnings

[5]In order to have one-year data for the out-of-sample rankings, we start the one-year backward rolling window rankings from the beginning of 1985. In addition, we also construct REG using the relative rankings of $DGTW$ and $AdjSUE$ within a five-year backward rolling window, which produce similar results to those with the one-year backward rolling window.

surprise ($AdjSUE_{i,t}$) and long-horizon abnormal return ($DGTW_{i,t:t+20}$) yields qualitatively similar results. We focus on the one-day return response since it is visible, capturing the attention of the media (and analysts) and directly tied to earnings, while longer horizon returns are confounded by other events that may occur.

2.2. Bias in Analyst Expectation and Firm Mispricing Measures

To explore the interplay between bias in analyst expectation and market reaction, we investigate the existence of biased analyst expectation from three different sets of the information reported to I/B/E/S by the analysts. They include earnings forecasts, price targets, and stock recommendations. Given that REG is directly connected to earnings forecasts, our main analyses will focus on analyst earnings forecast errors (AFE). In our additional tests, we also provide results using price target forecast errors (the implied return forecast errors, *RetForeErr*) and buy-and-sell recommendations changes (*RecChng*). Earnings forecasts reveal analysts' perception of a firm's future prospect, while recommendations and price targets forecasts provide direct information that investors can act on. Thus, we are able to explore the effect of REG on different dimensions of analyst output.

We obtain information about analysts' quarterly EPS forecasts, 12-month price target estimates, and buy and sell recommendations from the I/B/E/S database. Analyst forecast error (AFE) is the difference between the median of analysts' EPS forecast and the actual EPS, scaled by the standard deviation of analysts' EPS forecasts. Notice that, by construction, the value of AFE is exactly opposite to that of SUE for each stock i on earnings announcement day t.

Unlike earnings forecasts, future price target estimates issued and recommendations by analysts offer more straightforward and actionable guidance for investors. Future price targets scaled by current price provide an estimate of analyst return forecast of the stock. Using the 12-month price target estimates from the I/B/E/S database, we first obtain all the price target estimates issued by analysts over the subsequent 60 trading days following each earnings announcement. Then we estimate the analyst 12-month return forecast by scaling the future price target by the current stock price and subtracting 1 from the ratio. Next, we compute the actual 12-month return using the actual future price and current price. Finally, we calculate the average return forecast error (*RetForeErr*), which is the average of the difference between the forecast return minus the realized return across all analysts, and multiply the difference by 100 so that the return forecast error is expressed in percentage.

Recommendations from analysts offer investors explicit trading advice: strong buy, buy, hold, underperform, or sell. Each of them is assigned a numerical number in the I/B/E/S database, from 1 (strongly buy) to 5 (sell). We construct analyst recommendation change (*RecChng*) as the average of numerical change of recommendations issued by analysts during the following few weeks after the earnings announcement day. We multiply the change by -1 so that a positive (negative) change is associated with an optimistic (pessimistic) change.

Finally, as our main firm mispricing measure, We adopt the mispricing score of stocks from Stambaugh et al. (2015). The mispricing score (*MISP*) of a stock, ranging from 0 to 100, is an arithmetic average of ranking of the stock in 11 anomalies. For each anomaly, the stock would be ranked higher if the degree of over-pricing according to that anomaly is greater. Thus, the higher the value of a mispricing score, the greater the degree of over-pricing. We extend our analysis by using *MISP*'s *PERF* and *MGMT* anomaly groups as classified by Stambaugh and Yuan (2017), and by using van Binsbergen et al. (2021)'s *Build-Up* and *Resolution* anomaly classification. See Appendix B for detail.

2.3. Stock Controls

We construct the set of stock controls used in the regression analysis using information from both the CRSP and the I/E/B/S database following the standard literature. *LnSIZE* is the natural logarithm of the stock's size, which is the market capitalization of the stock in millions of dollars as of the end of the previous month. *LnBM* is the natural logarithm of the stock's book-to-market ratio. The size and book-to-market ratio are rebalanced every June following Fama and French (1992). *RET5* and *RET21* are stock's cumulative past returns from day t-5 to day t-1 and from day t-21 to day t-1, respectively. *MOM* is the momentum of the stock, which is the average of daily returns over the period from day t-251 to day t-21. *RET5*, *RET21*, and *MOM* are all expressed in percentages. *RVOL* is the realized volatility of the stock, defined as the square root of the annualized realized variance, which is 252 times the average squared daily returns from day t-21 to day t-1. *ILLIQ* is the Amihud (2002) illiquidity measure, which is the average ratio of absolute daily return by daily total dollar trading volume of stock from day t-21 to day t-1. *DISP* is the dispersion of analyst earnings forecasts, which is the standard deviation of analyst earnings forecasts scaled by the stock price. *NUMEST* denotes the number of analysts issuing earnings forecasts, which is the natural logarithm of one plus the number of analysts issuing forecasts.

Note that one of the key variables we are interested in, *MISP*, is observed on a monthly basis. Therefore, in the analysis with *MISP*, the daily stock control variables are recorded at the end of each month, instead of at the end-of-day. Thus, we also construct the following additional control variables. *MRET* is the monthly return in percentage. *MMOM* is the monthly momentum, which is the monthly returns in percentage over the past 11 months. *MRVOL* denotes the monthly realized volatility, which is defined as the standard deviation of monthly returns over the 12 months ending in each June. If at least 9 monthly returns are available, then the *MRVOL* is applied to the following 12 months, i.e., July of the same year to June of the next year. *MILLIQ* is the illiquidity of the month, which is the average daily Amihud (2002) illiquidity ratio over all trading days of the month.

2.4. Sample and Descriptive Statistics

Our sample period is 1985 to 2018, where 1985 is the first year for which we construct *REG* using one-year historical earnings data from the I/B/E/S database. We match the I/B/E/S tickers to CRSP using the ICLINK table.[6] As common in the literature, we shift an earnings announcement that occurs after market close to the next trading day. Our final sample includes 228,266 earnings announcements for 8,434 distinct stocks 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.

Table 2 provides descriptive statistics of our main variables. Panel A presents the time-series average of the cross-sectional mean, standard deviation, and quantiles for each variable. *REG* average is centered around zero. The average daily $DGTW$ abnormal return is also centered around zero. *SUE* (*AFE*) presents a positive (negative) average of 0.193(-0.193), consistent with Mendenhall (2004). The average mispricing score (*MISP*) is around 50, meaning that an average stock in our sample is fairly valued based on Stambaugh et al. (2012)'s metric.

Panel B of Table 2 reports the time-series average of the cross-sectional correlation of these main variables in our sample. Not surprisingly, *REG*, is positively correlated with $DGTW$ and negatively correlated with *SUE*, however, *REG* relative ranking contains relevant information beyond the mere values of $DGTW$ and *SUE*. At the same time, *REG* is positively

[6]The ICLINK table provides the mapping between I/B/E/S TICKER and CRSP PERMNO and is created following the WRDS Macro for ICLINK.

correlated with the mispricing score, *MISP*, indicating that stocks with a greater (lower) degree of over-pricing are more likely to experience investor overreaction (underreaction). Finally, the positive correlation between *SUE* and *DGTW* further confirms that investors are responding in the same direction as the sign of the earnings surprise in general.

3. *REG* and Formation of Beliefs

The *REG* measure is designed to capture the extent to which stock prices are responding disproportionately to earnings surprise, relative to the average response as captured by ranking. This response may be temporary if it is driven by noise, or relatively permanent if it is driven by investors' beliefs related to fundamental information (which is not reflected in *SUE*) or distorted beliefs that reflect aggregate valuation. To find out whether the difference between stock price response the earnings surprise is temporary or stable, we begin our investigation by analyzing the relation between *REG* and abnormal stock returns on day t (i.e., the earnings announcement day) and the subsequent 21 trading days. If *REG* is capturing investor beliefs, we should expect the market reaction on earnings announcement days to be persistent over the long period. We find that this is the case. Then to provide additional validation, we analyze the link between *REG* and institutional trading and show that institutional investors are net buyers on and after earnings announcement days when *REG* is high.

3.1. REG *and Abnormal Stock Returns*

To examine the relationship between *REG* and stock abnormal returns, we form portfolios sorted on *REG* and explore the return to a long-short strategy to illustrate the returns pattern and economic significance earned on a long-short portfolio.

We sort all stocks with earnings announcements reported on a given earnings announcement day t into deciles based on their level of REG. We then compute portfolio returns by equally-weighting the $DGTW$ abnormal return on day t ($DGTW_t$), the cumulative $DGTW$ abnormal return from day t+1 to day t+20 ($DGTW_{t+1:t+20}$), and the cumulative $DGTW$ abnormal return from day t to day t+ 20 ($DGTW_{t:t+20}$) of the stocks in each decile portfolio. In addition, we calculate the return on the high-minus-low (H-L) portfolio that longs stocks in the top decile with high REG and shorts stocks in the bottom decile with low REG.

The returns on decile portfolios and the high-minus-low portfolio for different horizons are displayed in Table 3. Rows 1 and 2 of Table 3 report day t $DGTW$ abnormal return for each decile portfolio as well as the high-minus-low portfolio, together with the number of earnings days used to calculate the averages. It is clear that the $DGTW$ abnormal return grows monotonically from -5.26% in the bottom decile to 5.14% in the top decile as the value of REG increases. The return on the high-minus-low portfolio would earn a $DGTW$ abnormal return of 10.40%. This is not surprising due to the construction of REG. It reflects the fact that a larger (smaller) value of REG is associated with a relatively higher (lower) market response. Rows 3-4 of Table 3 show the cumulative $DGTW$ abnormal return on each portfolio over the subsequent 20 trading days following day t, i.e., $DGTW_{t+1:t+20}$. On average, the return on the high-minus-low portfolio generates a cumulative $DGTW$ abnormal return of -1.19% over the next 20 trading days, which is about 11% reversal to the reaction on day t. This result lends support to the notion that the reversal following the market reaction on day t is relatively small. The cumulative $DGTW$ abnormal return $DGTW_{t:t+20}$ on decile and high-minus-low portfolios is presented in rows 5-6 of Table 3. On average, the return on a high-minus-low portfolio based on REG reaches a cumulative abnormal return of 9.21% after it has been held for 21 trading days since day t. It indicates that the market reaction on day t stays persistent for 21 trading days. Thus day t stock return response is reflecting investors' belief about firm prospects, where the small reversal is consistent with a liquidity shock (Da et al., 2014). Finally, the returns earned on the long and short legs of the H-L portfolios are qualitatively similar, suggesting that the market repose deviation captured by *REG* is not concentrated in positive or negative scenarios.[7]

In sum, the evidence from the abnormal returns provides support to the significance and persistence of the market reaction on the day of the earnings announcement. Although a return reversal is observed, it is relatively small (Da et al., 2014), supporting the idea that the gap between market reaction and firm's earnings information captures investors' belief about future firm prospects that are not captured by *SUE*.

3.2. REG *and Institutional Investors*

Investors reflect their beliefs into stock prices via trading. Thus, in this subsection, we explore the relation between the gap between market participants' reaction and earnings information and net trading by institutional investors. In particular, we investigate whether the large difference between market response and fundamental information captured by high *REG* is associated with a greater amount of net buying by institutional investors.

We obtain institutional trading data from the ANcerno Ltd. The data overlaps with our *REG* sample from February 2002 to December 2015. We measure institutional net buying with the net share from volume (*NSFV*), which is the institutional buying shares minus their selling shares from volume normalized by daily total share volumes. We employ Fama and

[7]We obtain similar results using a cross-sectional regression analysis, which controls for a wide set of firm characteristics. In particular, the coefficients on *REG* on day t, $t+1:t+20$, and $t:t+20$, are 18.615, -2.139, and 16.547, respectively. In addition, extending the window to 60 trading days shows that there is no continuation in the reversal.

MacBeth (1973) regression and explore the contemporaneous and predictive relationships between *REG* and *NSFV*.

$$NSFV_{i,t} = \gamma_{0,t} + \gamma_{emr,t} REG_{i,t} + \gamma_{sue,t} SUE_{i,t} + \gamma_{dgtw,t} DGTW_{i,t} + \sum_{k=1}^{K} \gamma_{k,t} Z_{k,i,t} + \epsilon_{i,t} \qquad (4)$$

and

$$NSFV_{i,t+1:t+d} = \gamma_{0,t} + \gamma_{emr,t} REG_{i,t} + \gamma_{sue,t} SUE_{i,t} + \gamma_{dgtw,t} DGTW_{i,t} + \sum_{k=1}^{K} \gamma_{k,t} Z_{k,i,t} + \epsilon_{i,t} \qquad (5)$$

where $NSFV_{i,t}$ is the net share from volume by institutional investors on day t, and $NSFV_{i,t+1:t+d}$ denotes the cumulative net shares from volume by institutional investors over the period from day $t+1$ to $t+d$ ($d = 5, 10, 15$). Stock control variables include *LnSIZE*, *LnBM*, *RET5*, *RET21*, *MOM*, *RVOL*, and *ILLIQ*. See table 1 for more details about variable definitions. Finally, given that the number of firms reporting their earnings is very scarce on some days; in the second stage of the Fama-MacBeth procedure, we report value-weighted averages based on the daily number of cross-sectional observations.

Table 4 present the regression results. We begin with the analysis of the contemporaneous relation between *REG* and *NSFV* (column 1). The *REG* coefficient estimate indicates that institutional investors' net buying is positively and significantly correlated with *REG* on the day of the earnings announcement. Note that this relation holds after controlling for *SUE* and *DGTW*, reflecting the partial association between *REG* and net institutional trading.

Next, we look into the trading behaviors of institutional investors during the subsequent d trading days ($d = 5, 10, 15$). The predictive regression results in columns (2) - (4) of Table

4 indicate that institutional investors continue to be net buyers of stocks with positive *REG*. This further supports the argument that investors do not change their beliefs about the firm. Economically, a change in *REG* from its 25^{th} percentile to 75^{th} percentile results in an increase in institutional net buying shares by 2.152% ($= (0.114 - (-0.113)) \times 9.481$) of trading volume over the next five days, which is approximately 0.430% for each day, equivalent to 9.45% ($= 0.430/(2.670 - (-1.880))$) of the difference between the 25^{th} percentile and the 75^{th} percentile of *NSFV*. Finally, while the cumulative trading attenuates in the third week, the prediction for cumulative *NSFV* over a longer period than 15 days indicates that the effect of *REG* on *NSFV* is only partially reversed.

Taken together, our results thus far have demonstrated that the gap between the firm's earnings fundamentals and the market reaction measured by *REG* is consistent of a reflection for investors' beliefs.

3.3. *Biased Analyst Expectation*

3.3.1. *The Effect of* REG *on* AFE

The link between anomaly returns and analyst forecasting errors (*AFE*) has been growing rapidly since the early findings by La Porta (1996). In particular, analysts have been found to be overly optimistic (pessimistic) for anomaly shorts (longs). Given the importance of analyst earnings forecasts, which reflect their beliefs, in this subsection, we investigate whether market reaction has any implication for the accuracy of analyst forecasts in the following quarters. Specifically, if analysts can disentangle the noise and information from market participants' earnings reactions, we should not expect to find any predictive relation, or even a reduction in the analyst earnings forecast bias if *REG* conveys relevant fundamental information.

We explore the effect of *REG* on the bias in analyst forecast errors (*AFE*) using Fama and MacBeth (1973) cross-sectional regression. We use REG in quarter q to predict AFE over the subsequent quarters up to quarter q+12.

$$\begin{aligned} AFE_{i,q+n} &= \gamma_{0,t} + \gamma_{emr,t} REG_{i,t(q)} + \gamma_{afe,t} AFE_{i,t(q)} + \\ & \gamma_{dgtw,t} DGTW_{i,t(q)} + \gamma_{misp,t} MISP_{i,t(q)} + \sum_{k=1}^{K} \gamma_{k,t} Z_{k,i,t} + \epsilon_{i,t} \end{aligned} \tag{6}$$

where $AFE_{i,q+n}$ is the analyst earnings forecast error of stock i for the earnings announcement q quarters ahead (n=1, ...12). $REG_{i,t}$, $AFE_{i,t}$, $DGTW_{i,t}$ are market misreaction, analyst earnings forecast errors, and DGTW-adjusted daily abnormal return of stock i on earnings announcement day t in quarter q. $MISP_{i,t}$ is the Stambaugh et al. (2015) monthly mispricing score of the month of the earnings announcement. Stock control variables include *LnSIZE*, *LnBM*, *RET5*, *RET21*, *MOM*, *RVOL*, *ILLIQ*, *DISP*, and *NUMEST*. See table 1 for more details about variable definitions. Given that the number of firms reporting their earnings is very scarce on some days, we report value-weighted averages based on the daily number of cross-sectional observations in the second stage of the Fama-MacBeth procedure.

The results are presented in Table 5. We control for lagged AFE and $DGTW$ to address the concern about the persistence in analysts forecasting errors and the impact of past returns. We also control for *MISP* to account for the relation between analyst forecasting errors and firm mispricing documented in previous studies. In all regressions, the coefficient on REG are positive and significant, implying the positive impact of REG on future analyst earnings forecast error. The predictive relation of REG decays from quarter 1 to quarter 12, which is expected given that new information enters into the calculation of the analysts' forecasts. Specifically, the coefficient on REG ranges from 2.464 (t-statistics, 11.93) in the prediction of quarter q+1 to 0.979 (t-statistics, 4.10) in the prediction of quarter q+12. Note that this is beyond the persistence in AFE, which is reflected in the positive relation between AFE in quarter q and AFE over the subsequent 12 quarters.

Next, we assess the economic significance of *REG*. Given the relation between firm mispricing and analyst earnings forecast errors, we are specifically interested in comparing the effect of *REG* and *MISP* on AFE in subsequent quarters. Take for example, the AFE one quarter ahead (column (1) of Table 5). A change in *REG* from its 25^{th} percentile to 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 the difference between the 25^{th} percentile to the 75^{th} percentile in AFE. As a comparison, the coefficient on *MISP* is 0.016, which means that a change in *MISP* from its 25^{th} percentile to 75^{th} percentile is resulting in a rise in the next quarter's AFE by 0.278 $(= (58.779 - 41.404) \times 0.016)$, which is equivalent to 10.49% $(= 0.278/(0.829 - (-1.820)))$ of the change from the 25^{th} percentile to the 75^{th} percentile of AFE. This shows that the economic significance of the impact of *REG* on next quarter's analyst earnings forecast error is nearly twice as large as that of the mispricing score.

Overall, the findings above suggest that when forming expectations, analysts take into account how the market reacts to fundamental news. In particular, they suggest that analysts cannot disentangle the noise from information and market participants' reaction to earnings information feeds back into and distorts the analysts' expectation formation. in the next subsection, we further explore the interaction between AFE and *REG* and show that results in slower convergence of analyst forecasting error.

3.3.2. Confirmation Bias and the Convergence of Biased Analyst Expectation

A natural question to ask is why analysts cannot disentangle the noise that is present in *REG*, and use the information reflected in the EPS to adjust their subsequent forecasts. One explanation suggested in the literature is "confirmation bias" (Pouget et al., 2017; Cookson et al., 2021; Hirshleifer et al., 2021). In our setting, this would suggest that analysts interpret the market response as a confirmation of their own expectations.

We provide evidence that is consistent with the consumption of confirmatory information. Specifically, we analyze the effect of *REG* on the speed of convergence of *AFE* over subsequent quarters, in cases where *REG* confirms (same sign) or disconfirms (opposite sign) *AFE*. At the end of each month in our sample, we assign all stock-earnings announcement observations into four portfolios according to the direction of *AFE* and the confirmation of *REG* in terms of their sign: 1) confirmed positive *AFE* ($AFE>0$ & $REG>0$); 2) disconfirmed positive *AFE* ($AFE>0$ & $REG<0$); 3) confirmed negative *AFE* ($AFE<0$ & $REG<0$); and 4) disconfirmed negative *AFE* ($AFE<0$ & $REG>0$).[8] Next, we construct a long-short strategy for confirmed (disconfirmed) portfolios that longs the positive confirmed (disconfirmed) portfolio and shorts the negative confirmed (disconfirmed) portfolio and explore the *AFE* of each long-short strategy over subsequent quarters.

Table 6 presents the *AFE*'s for each long-short strategy in 1, 2, 3, 4, 8, and 12 quarters ahead. In the cases where *REG* confirms *AFE* in terms of the sign, the errors are always greater than the case when they are in the opposite direction. Thus, the convergence of *AFE* is much slower when *REG* confirms *AFE*. To give economic meaning, we compute the difference between the long-short strategies on confirmed and disconfirmed portfolios relative to the disconfirmed base. We show that the errors of a long-short portfolio of *AFE* that has

[8] Performing the analysis at the daily level would lead to an insufficient number of observations.

confirmatory information are 21.38% larger in the next quarter and up to 45.96% larger in subsequent quarters. In other words, the exploration of *AFE*'s in subsequent quarters shows that the convergence of analysts' biased expectation is much slower when *REG* "confirms" *AFE*.

4. The Mispricing Cycle

4.1. The Effect of REG *on* MISP

So far, we have shown that investors' reaction to earnings information results in a greater bias in analyst earnings forecasts over the subsequent quarters. We also confirmed the relation between firm mispricing (*MISP*) and analyst earnings forecasting errors (*AFE*). In this subsection, we examine the predictive relation between investors' reaction to earnings information (*REG*) and subsequent firm mispricing scores.

As in previous tests, we employ the Fama and MacBeth (1973) regression for predicting *MISP* in the quarters following each earnings announcement.

$$\begin{aligned} MISP_{i,q+n} &= \gamma_{0,t} + \gamma_{emr,t} REG_{i,t(q)} + \gamma_{afe,t} AFE_{i,t(q)} + \\ &\quad \gamma_{dgtw,t} DGTW_{i,t(q)} + \gamma_{misp,t} MISP_{i,t(q)} + \sum_{k=1}^{K} \gamma_{k,t} Z_{k,i,t} + \epsilon_{i,t} \end{aligned} \tag{7}$$

where $MISP_{i,q+n}$ is the Stambaugh et al. (2015) monthly mispricing score observed at the end of each quarter, n quarters ahead. $REG_{i,t}$, $AFE_{i,t}$, and $DGTW_{i,t}$ are the return earnings gap, analyst earnings forecast, and DGTW-adjusted abnormal return as of earnings announcement day t in quarter q. $MISP_{i,t(q)}$ denotes the Stambaugh et al. (2015) monthly mispricing score as of the month of earnings announcement day t in quarter q. Stock control variables include

LnSIZE, *LnBM*, *MRET*, *MMOM*, *MRVOL*, and *MILLIQ*. See table 1 for more details about variable definitions. All stock controls are recorded as of the end of the month of day t. As done in previous analyses, we compute the time-series observation-weighted average of each slope coefficient.

We predict *MISP* in 1, 2, 3, 4, 8, and 12 quarters ahead and report the results in Table 7. As in Table 5, we account for the dependent variable persistence, where the persistence declines from 0.841 (Column 1) to 0.409 (Column 6). Exploring the effect of *REG* on *MISP*, the collective results clearly indicate that *REG* has a significant and positive influence on firm mispricing. Starting with *MISP* in quarter q+1, a change in *REG* from its 25^{th} percentile to 75^{th} percentile results in a rise in the *MISP* of 0.523 $(= (0.114 - (-0.113)) \times 2.304)$. For comparison, the increase in *MISP* caused by a change from the 25^{th} percentile to the 75^{th} percentile in *AFE* is 0.156 $(= (0.829 - (-1.820)) \times 0.059)$. Thus, in a horse race between *REG* and *AFE*, the effect of *REG* is over three times that of *AFE*. Given the ample evidence and discussions in the literature on the relation between *AFE* and firm mispricing, this comparison establishes that the effect of *REG* on *MISP* warrants attention.

Another interesting observation that emerges from the comparison between *REG* and *AFE* over time, is that the *REG* effect increases up to 4 quarters ahead, while the effect of *AFE* declines starting 2 quarters ahead. This comparison suggests that on a timeline, *REG* is able to better predict the mispricing build-up stage, while *AFE* comes at a later stage, where mispricing is present. For example, comparing the economic effect of *AFE* and *REG* after 3 quarters (Column (3) of Table 7), an increase in *REG* from its 25^{th} percentile to 75^{th} percentile would lead to an increase in the *MISP* of 0.681 $(= (0.114 - (-0.113)) \times 2.999)$. In contrast, the effect of *AFE* is 0.106 $(= (0.829 - (-1.820)) \times 0.040)$.

In order to have a better understanding of the cycle of mispricing captured by *REG* predictability, we plot the effect of *REG* on *MISP* over three years in Figure 1. Specifically, we draw the time-series plot for the estimations and the corresponding 95% confidence intervals of coefficients on *REG* in the *MISP* predicting regressions. As depicted in the figure, the influence of investors' reaction to a stock's earnings surprise is positively impacting its degree of mispricing in the subsequent quarters. The effect gradually escalates and peaks in the third quarter following the earnings announcement. After that, it attenuates sharply and decays to be no longer significant after 12 quarters. In a word, this figure provides a graphic representation of the cyclic pattern of the effect of *REG* on *MISP*.

4.2. Anomaly Dissection

In this section, we further explore the effect of *REG* on stock mispricing by examining the impact of *REG* on different groupings of asset pricing anomalies. We start by following Stambaugh and Yuan (2017) and dissecting the 11 anomalies, which are building blocks of the *MISP* score, into two clusters: management (*MGMT*) and performance (*PERF*). Then we closely follow the average anomaly ranking approach of Stambaugh et al. (2015) and average the stock's rankings according to the anomalies within each cluster. Thus, we have two mispricing measures: $MISP_{MGMT}$ and $MISP_{PERF}$. Similarly, we obtain the anomalies from van Binsbergen et al. (2021), who classify asset pricing anomalies into those that exacerbate mispricing (*Build-Up*) and those that resolve mispricing (*Resolution*), and construct another two mispricing measures with respect to build-up and resolution anomalies: $MISP_{BUILD}$ and $MISP_{RES}$. [9]

We repeat the predictions in Eq. (7) by replacing the *MISP* with the new mispricing

[9] The stock-level anomaly data is obtained from Chen and Zimmermann (2021) Asset Pricing Open Source dataset. Details about the matching for anomalies to Chen and Zimmermann (2021) stock-level characteristics as well as the ranking procedure are given in Appendix B.1.

scores associated with four classes of anomalies: $MISP_{MGMT}$, $MISP_{PERF}$, $MISP_{BUILD}$, and $MISP_{RES}$. The coefficients on REG for predicting the misprcing scores in 1, 2, 3, 4, 8, and 12 quarters ahead are presented in Table 8. As clearly shown in the table, REG is positively predicting $MISP_{MGMT}$ up to 4 quarters ahead in a significant way and it peaks in 1 year ahead. For longer forecasting horizons (8 and 12 quarter ahead), the coefficients on REG drop and become insignificant with t-statistics no greater than 1.29. On the contrary, the coefficient on REG declines gradually when predicting $MISP_{PERF}$ in 1, 2, 3, 4, 8, and 12 quarters ahead. In general, the dissection of *MISP*'s underlying 11 anomalies into $MGMT$ and $PERF$ anomalies demonstrate that the positive impact of REG on stock misprcing still holds for $MISP_{MGMT}$ and $MISP_{PERF}$, which also connects to the two mispricing factors in Stambaugh and Yuan (2017). Besides, the observations about the persistence of REG's coefficient confirm the long (short) nature of the characteristics constituting $MGMT(PERF)$. That is, $MISP_{MGMT}$ takes time to reach its peak, while $MISP_{PERF}$ is reflected quickly in the scores and then decays.

Next, we find a stark difference between the *Build-Up* and *Resolution* anomaly classification. In the predictions of future $MISP_{BUILD}$, the results from all regressions indicate a positive and significant effect of REG on stock mispricing. Moreover, we find that it takes up to 2-years for the mispricing to reach its peak. These results align with the finding by van Binsbergen et al. (2021) that build-up anomalies are resulting from continuing over-pricing and slow correction and therefore drive the stock price further away from its fundamental. When predicting $MISP_{RES}$, the coefficient on REG are all negative and significant, suggesting that a high REG predicts the attenuation of stock mispricing. This is in line with the notion that resolution anomalies are resolving existing mispricing and alleviating price dislocation. Altogether, the comparison between the effect of REG on $MISP_{BUILD}$ and $MISP_{RES}$ implies that *REG* is an important signal in predicting the exacerbation of misprcing for build-up anomalies and the onset of the correction of mispricing for resolution anomalies.

To have a better understanding of the pattern of the impact of *REG* on mispricing over time, we plot the coefficients on *REG* for predicting each misprcing score in 1, 2, 3, 4, 8, and 12 quarters ahead in Figure 2. The top figure illustrates the coefficient on *REG* and the corresponding 95% confidence intervals when predicting $MISP_{MGMT}$ and $MISP_{PERF}$. The differences between $MISP_{MGMT}$ and $MISP_{PERF}$ can be clearly seen, where the impact of *REG* on future $MISP_{PERF}$ is decaying over time, while the predictions for $MISP_{MGMT}$ exhibits a cyclic pattern as the forecasting horizon extends. Likewise, the impact of *REG* on stock mispricing is also following a pattern of a cycle for *Build-Up* anomalies, where at the same time there is a clear negative relation for the *Resolution* of mispricing anomalies.

5. The Determinants of *REG* and Dynamic Interrelations

5.1. *The Determinants of* REG

Next, we turn our investigation to the factors that possibly contribute to the observed gap between investors' reaction and earnings fundamentals. In particular, we assess the predictive relation of the bias in analyst expectation (*AFE*) and firm mispricing (*MISP*) on *REG*.

We employ Fama and MacBeth (1973) regressions to predict *REG* in the next quarter, REG_{q+1}, for all stock-earnings announcement observations in our sample.

$$\begin{aligned} REG_{i,q+1} &= \gamma_{0,t} + \gamma_{afe,t} AFE_{i,t(q)} + \gamma_{misp,t} MISP_{i,t(q)} + \\ & \gamma_{emr,t} REG_{i,t(q)} + \gamma_{dgtw,t} DGTW_{i,t(q)} + \sum_{k=1}^{K} \gamma_{k,t} Z_{k,i,t} + \epsilon_{i,t}, \end{aligned} \tag{8}$$

where $REG_{i,q+1}$ denotes the REG on the next earnings announcement quarter. $AFE_{i,t(q)}$, $REG_{i,t(q)}$, and $DGTW_{i,t(q)}$ are the analyst forecast error, return earnings gap, and DGTW-adjusted daily abnormal return of stock i observed at the end of the current earnings announcement day t in quarter q. *MISP* is the Stambaugh et al. (2015) monthly mispricing score of the stock i for the month of current earnings announcement day t. Stock control variables include *LnSIZE*, *LnBM*, *RET5*, *RET21*, *MOM*, *RVOL*, *ILLIQ*, *DISP*, and *NUMEST*. See table 1 for more details about variable definitions. As done in previous analyses, we obtain the slope coefficients from the cross-sectional regression and compute the time-series observation-weighted average of each slope coefficient. Table 9 presents the results.

The positive and significant coefficients on AFE and *MISP* suggest that stocks with a positive analyst bias and high mispricing scores are more likely to experience a positive overreaction by investors in the next quarter. The results in column (4) show that the positive effect of AFE and *MISP* on REG in the next quarter remains intact after controlling for the REG and the daily abnormal return on the current earnings announcement day t. The coefficient on AFE is 0.003 with a t-statistics of 13.26, implying that a change in AFE from its 25^{th} percentile to 75^{th} percentile would result in an increase of 0.008 $(= (0.829 - (-1.820)) \times 0.003)$ in REG, which is 3.52% $(= 0.008/(0.114 - (-0.113)))$ of the difference between the 25^{th} percentile to 75^{th} percentile of REG. In the meanwhile, the coefficient of 0.0004 on *MISP* with a t-statistics of 10.05 indicates that the mispricing score has additional influence on future REG. In an economic sense, it shows that when *MISP* rises from its 25^{th} percentile to 75^{th} percentile, it will lead to an increase of 0.007 $(= (58.779 - 41.404) \times 0.0004)$ in REG, which is about 3.08% $(= 0.007/(0.114 - (-0.113)))$ of the gap between the 25^{th} percentile and the 75^{th} percentile of REG.

Interestingly, we also find that the past month's returns (*RET21*) and the earnings announcement day return ($DGTW$) negatively predict REG. This is consistent with the correction phase documented in Engelberg et al. (2018), and further highlights the difference between "raw" returns and the relative ranking captured by REG.

The evidence documented above suggests that both biased analyst expectation and stock's mispricing contribute to future investors' (mis)reaction to earnings information. In other words, a stock with greater (smaller) analyst earnings forecast error and a higher (lower) degree of over-pricing would be exposed to more pronounced investor overreaction (underreaction) to earnings surprise. The findings we have established so far indicate a dynamic amplification effect where higher REG leads to greater AFE and $MISP$, which in turn lead to higher REG.

5.2. *Impulse Response*

To further examine the dynamic relation between AFE, $MISP$, and REG, we plot the impulse responses of AFE, $MISP$, and REG to a one-standard-deviation shock to these variables. We estimate a quarterly vector autoregression (VAR) system of AFE, $MISP$, and REG, with four lags of each variable. The regressions include the full set of firm control variables together with firm fixed effects and quarter fixed effects. The VAR system allows no current quarter shocks to enter the system and affect the variables. Therefore, the responses are only based on the lags of the system. Each graph in Figure 3 plots the response of AFE, $MISP$, and REG to shocks in the other two variables in the subsequent $0, 1, 2, ..., 12$ quarters, respectively.

The first graph in Figure 3 depicts the cumulative response of AFE to a one-standard-deviation shock in REG and $MISP$. As shown in the plot, both REG and $MISP$ are positively affecting AFE in the following quarters. Also, it can be seen that the impulse response of AFE to a one standard deviation shock in REG is nearly five times as the response of AFE induced to a one-standard-deviation shock in *MISP*.

Next, the response of *MISP* to shocks in *REG* and *AFE* is shown in the second graph. It is clearly illustrated that while *MISP* is reacting positively to a one standard deviation shock in both *REG* and *AFE*, the impact of *REG* is much larger than that of *MISP*. Given the close connection between *AFE* and *MISP*, the observations above provide further supporting evidence for the economic importance of the impact of *REG* on future *AFE* and *MISP*. The last graph shows the response of *REG* to shocks in *AFE* and *MISP*. Consistent with the findings in Section 5.1, a one standard deviation shock in both *AFE* and *MISP*leads to a positive response in *REG* in the following quarters, indicating that a stock with greater *AFE* and *MISP* is exposed to more pronounced *REG* afterward.

6. Additional Results

6.1. Positive and Negative Market Misreaction

As evidenced in the extant literature, investor optimism can induce stock misvaluation to a greater extent than pessimism due to the asymmetric ease of buying versus shorting (Stambaugh et al., 2012). Thus, we examine whether the effect of *REG* on various variables is concentrated on one side. While the portfolio analysis reported in Table 3 indicates a balanced effect, in this subsection we repeat our main analysis using positive and negative *REG* splits.

We first generate two dummy variables, one for positive values of *REG* (Dummy(REG>0)) indicating an overreaction on the positive side. And a negative *REG* dummy (Dummy($REG \leqslant 0$)) indicating an overreaction on the negative side. respectively. We then repeat the investigation of the effect of *REG* on next quarter's *AFE* and next quarter's *MISP* by replacing *REG* in Eq.

(6) and Eq. (7) with *REG**Dummy(*REG*>0), *REG**Dummy(*REG*$\leqslant$0), and Dummy(*REG*>0).

The prediction for next quarter's *AFE* and *MISP* are presented in Table 10. Columns (1) - (4) show the prediction for *AFE* with current *AFE*, *DGTW*, *MISP*, and stock characteristics as controls. Focusing on column (4), the coefficient on the positive *REG* and negative *REG* interaction terms are 2.704 (t-statistics, 8.20) and 2.184 (t-statistics, 7.02), respectively. It suggests that the positive impact of *REG* on next quarter's *AFE* is not dominated by either positive or negative *REG*s. Moreover, the fact that the coefficient on positive *REG* is larger and can support the general findings regarding the short-leg of anomalies, however, the difference between the coefficients of 0.52 is not statistically significant (t statistics, 1.33). Next, columns (5) - (7) display the results for *MISP* prediction. It is clearly shown that the coefficients on both the positive *REG* and negative *REG* interaction terms are positive and statistically significant, which means that the positive influence of *REG* on *MISP* we documented earlier is not triggered entirely by positive *REG*s or negative *REG*s. Interestingly, the difference between *REG* coefficient estimates of 1.281 is statistically significant (t statistics, 3.46) and in line with (Stambaugh et al., 2012) findings.

In a nutshell, the comparison between positive and negative *REG*s demonstrates that the effect of *REG* on future analyst earnings forecast error and stock's mispricing score is prevalent for both positive and negative *REG*s. The tilt toward the positive side of *REG* is expected and strengthens our findings of the link between market participants' beliefs, analysts' beliefs, and anomaly returns.

6.2. Other Aspects of Analyst Expectations

Thus far, our analysis reveals a robust relation between *REG* and *AFE*. In this subsection, we examine whether other outputs provided by analysts are affected by *REG*. In particular, we focus on analysts' price targets and stock recommendations. Both provide explicit and direct information that investors can act on. Overall, we find consistent results with the findings reported using *AFE*, where an increase in *REG* predicts higher price targets (i.e., positive return forecast errors), and positive recommendation changes.

6.2.1. Analyst Return Forecast Errors

We explore the relation between analysts' price targets and *AFE* using Fama and MacBeth (1973) regression for predicting the analyst implied return forecast error based on their 12-month price targets. In particular, we focus on price targets that occur *after* the quarterly earnings announcement, allowing analysts to be affected by *REG*. Given that analysts may not issue their price targets immediately after the earnings announcement, we track all analysts' price targets over a window of 60 trading days after the earnings announcement, and calculate the average (i.e., the consensus). Our regression takes the following form

$$\begin{aligned} RetForeErr_{i,t+1:t+60} =& \gamma_{0,t} + \gamma_{emr,t} REG_{i,t(q)} + \gamma_{afe,t} AFE_{i,t(q)} + \\ & \gamma_{dgtw,t} DGTW_{i,t(q)} + \sum_{k=1}^{K} \gamma_{k,t} Z_{k,i,t} + \epsilon_{i,t} \end{aligned} \tag{9}$$

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 market misreaction, analyst earnings forecast error, and DGTW-adjusted daily abnormal return of stock i as of the earnings announcement day t in quarter q. Stock control variables include *LnSIZE*, *LnBM*, *RET5*, *RET21*, *MOM*, *RVOL*, *ILLIQ*, and *NUMEST*. See table 1 for more details about variable definitions. 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 11. 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. On one hand, this might reduce the noise induced by a single analyst, on the other hand as observed, this limits the number of observations. For example, requiring at least 2 analysts, the coefficient rises to 3.267 and it is still statistically significant. A change in *REG* from its 25^{th} percentile to 75^{th} percentile would induce an increase in analyst return forecast error of 0.742% $(= (0.114 - (-0.113)) \times 3.267)$.

6.2.2. Analyst Recommendation Changes

Similar to the analysis of analyst price targets, we examine how analysts update their recommendations after observing investors' (mis)reaction on earnings announcement days. We run the Fama and MacBeth (1973) regression for average recommendation changes of analysts during the subsequent three weeks after the earnings announcement.

$$\begin{aligned} RecChng_{i,t+b:t+d} =& \gamma_{0,t} + \gamma_{emr,t} REG_{i,t(q)} + \gamma_{afe,t} AFE_{i,t} + \\ & \gamma_{dgtw,t} DGTW_{i,t(q)} + \sum_{k=1}^{K} \gamma_{k,t} Z_{k,i,t} + \epsilon_{i,t} \end{aligned} \tag{10}$$

where $RecChng_{i,t+b:t+d}$ denotes the average of recommendation changes issued by analysts from b day ahead to d day ahead of the earnings announcement day t in quarter q. Stock control variables include *LnSIZE*, *LnBM*, *RET5*, *RET21*, *MOM*, *RVOL*, *ILLIQ*, and *NUMEST*. See table 1 for more details about variable definitions. 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 12 reports the regression results. Similar to the findings documented with *AFE* and *RetForeErr*, *RecChng* also tends to be more positive following a positive *REG*. This provides additional support for the notion that analyst would revise their expectation based on market reaction to earnings information, and market misreaction would lead to distortion in analyst expectation formation.

In sum, the observations with *RetForeErr* and *RecChng* are consistent with our main findings in Section 3.3.1. It shows that a higher *REG* results not only in an increase in *AFE* but also in greater analyst return forecast errors and upward recommendation changes. This provides further validation for the argument that *REG* is positively impacting the bias in analyst expectations.

7. Conclusion

How investors form their expectations and the effect of their expectations on asset prices have been in the interest of academic research over the last several decades. Recent research highlight cognitive and other constraints that lead to biased expectation formation.

In this paper, we provide new empirical evidence, which adds to this growing line of research. We show that investors are likely to take into account the (biased) actions of other investors when forming their expectations. Consequently, expectations formation across investors is a dynamic process, which feeds back and results in an amplification effect of investors' initial bias.

Using a new measure that captures market participants' response to earnings information, we explore the dynamic reaction between investors who trade and reflect their beliefs when earnings information is released by the firm and analysts who provide their expectations about future firm earnings. We uncover a positive dynamic relation between market participants' reaction to earnings, analyst earnings forecast errors, and the degree of firm mispricing. In particular, we show that analysts' forecast errors are slower to converge when the market reaction to earnings confirms their views. We also show that market participants' initial reaction to earnings can predict the buildup stage in firm mispricing, which takes up to three years to revert fully and is more pronounced for "*Build-Up*" anomalies.

Overall, the dynamics that we document suggest that investors are affected by the biased belief formation of other investors. These findings contribute to the understanding of investors' beliefs formation and their effect on asset prices. In particular, they demonstrate the potential spillover effects in investors' expectation formation, which result in an amplification effect. They also add to the ongoing debate on the source of anomaly returns. Future research should consider these dynamics and further assess their impact on trading and asset prices.

References

Amihud, Y. 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5(1):31–56.

Baker, M. and Wurgler, J. 2006. Investor sentiment and the cross-section of stock returns. *Journal of Finance*, 61(4):1645–1680.

Bernard, V. L. and Thomas, J. K. 1989. Post-earnings-announcement drift: delayed price response or risk premium? *Journal of Accounting Research*, 27:1–36.

Bernard, V. L. and Thomas, J. K. 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics*, 13(4):305–340.

Birru, J., Mohrschladt, H., and Young, T. 2020. Disentangling anomalies: Risk versus mispricing. *Fisher College of Business Working Paper*, (2020-03):029.

Bordalo, P., Gennaioli, N., La Porta, R., and Shleifer, A. 2019. Diagnostic expectations and stock returns. *Journal of Finance*, 74(6):2839–2874.

Brav, A. and Lehavy, R. 2003. An empirical analysis of analysts' target prices: Short-term informativeness and long-term dynamics. *Journal of Finance*, 58(5):1933–1967.

Cassella, S. and Gulen, H. 2018. Extrapolation bias and the predictability of stock returns by price-scaled variables. *Review of Financial Studies*, 31(11):4345–4397.

Chan, L. K., Jegadeesh, N., and Lakonishok, J. 1996. Momentum strategies. *Journal of Finance*, 51(5):1681–1713.

Chen, A. Y. and Zimmermann, T. (Forthcoming) 2021. Open source cross sectional asset pricing. *Critical Finance Review*.

Cookson, J. A., Engelberg, J., and Mullins, W. 2021. Echo chambers. *Available at SSRN 3603107*.

Cready, W. M. and Gurun, U. G. 2010. Aggregate market reaction to earnings announcements. *Journal of Accounting Research*, 48(2):289–334.

Da, Z., Huang, X., and Jin, L. J. 2021. Extrapolative beliefs in the cross-section: What can we learn from the crowds? *Journal of Financial Economics*, 140(1):175–196.

Da, Z., Liu, Q., and Schaumburg, E. 2014. A closer look at the short-term return reversal. *Management science*, 60(3):658–674.

Da, Z. and Schaumburg, E. 2011. Relative valuation and analyst target price forecasts. *Journal of Financial Markets*, 14(1):161–192.

Daniel, K., Grinblatt, M., Titman, S., and Wermers, R. 1997. Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance*, 52(3):1035–1058.

De Long, J. B., Shleifer, A., Summers, L. H., and Waldmann, R. J. 1990. Positive feedback investment strategies and destabilizing rational speculation. *Journal of Finance*, 45(2):379–395.

Edelen, R. M., Ince, O. S., and Kadlec, G. B. 2016. Institutional investors and stock return anomalies. *Journal of Financial Economics*, 119(3):472–488.

Engelberg, J., McLean, R. D., and Pontiff, J. 2018. Anomalies and news. *Journal of Finance*, 73(5):1971–2001.

Engelberg, J., McLean, R. D., and Pontiff, J. 2020. Analysts and anomalies. *Journal of Accounting and Economics*, 69(1):101249.

Fama, E. F. and French, K. R. 1992. The cross-section of expected stock returns. *Journal of Finance*, 47(2):427–465.

Fama, E. F. and MacBeth, J. D. 1973. Risk, return, and equilibrium: empirical tests. *Journal of Political Economy*, 81(3):607–636.

Frankel, R. and Lee, C. M. 1998. Accounting valuation, market expectation, and cross-sectional stock returns. *Journal of Accounting and Economics*, 25(3):283–319.

Greenwood, R. and Shleifer, A. 2014. Expectations of returns and expected returns. *Review of Financial Studies*, 27(3):714–746.

Grossman, S. 1976. On the efficiency of competitive stock markets where trades have diverse information. *Journal of Finance*, 31(2):573–585.

Hartzmark, M. S. and Shue, K. 2018. A tough act to follow: Contrast effects in financial markets. *Journal of Finance*, 73(4):1567–1613.

Hayek, F. A. 1945. The use of knowledge in society. *American Economic Review*, 35(4):519–530.

Hirshleifer, D., Lourie, B., Ruchti, T. G., and Truong, P. 2021. First impression bias: Evidence from analyst forecasts. *Review of Finance*, 25(2):325–364.

Holthausen, R. W. and Verrecchia, R. E. 1988. The effect of sequential information releases on the variance of price changes in an intertemporal multi-asset market. *Journal of Accounting Research*, 26(1):82–106.

Hughes, J., Liu, J., and Su, W. 2008. On the relation between predictable market returns and predictable analyst forecast errors. *Review of Accounting Studies*, 13(2):266–291.

Jegadeesh, N., Kim, J., Krische, S. D., and Lee, C. M. 2004. Analyzing the analysts: When do recommendations add value? *Journal of Finance*, 59(3):1083–1124.

Kozak, S., Nagel, S., and Santosh, S. 2018. Interpreting factor models. *Journal of Finance*, 73(3):1183–1223.

La Porta, R. 1996. Expectations and the cross-section of stock returns. *Journal of Finance*, 51(5):1715–1742.

La Porta, R., Lakonishok, J., Shleifer, A., and Vishny, R. 1997. Good news for value stocks: Further evidence on market efficiency. *Journal of Finance*, 52(2):859–874.

Livnat, J. and Mendenhall, R. R. 2006. Comparing the post–earnings announcement drift for surprises calculated from analyst and time series forecasts. *Journal of Accounting Research*, 44(1):177–205.

Mendenhall, R. R. 2004. Arbitrage risk and post-earnings-announcement drift. *Journal of Business*, 77(4):875–894.

Mian, G. M. and Sankaraguruswamy, S. 2012. Investor sentiment and stock market response to earnings news. *Accounting Review*, 87(4):1357–1384.

Newey, W. and West, K. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3):703–08.

Nickerson, R. S. 1998. Confirmation bias: A ubiquitous phenomenon in many guises. *Review of General Psychology*, 2(2):175–220.

Pouget, S., Sauvagnat, J., and Villeneuve, S. 2017. A mind is a terrible thing to change: confirmatory bias in financial markets. *Review of Financial Studies*, 30(6):2066–2109.

So, E. C. 2013. A new approach to predicting analyst forecast errors: Do investors overweight analyst forecasts? *Journal of Financial Economics*, 108(3):615–640.

Stambaugh, R. F., Yu, J., and Yuan, Y. 2012. The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, 104(2):288–302.

Stambaugh, R. F., Yu, J., and Yuan, Y. 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. *Journal of Finance*, 70(5):1903–1948.

Stambaugh, R. F. and Yuan, Y. 2017. Mispricing factors. *Review of Financial Studies*, 30(4):1270–1315.

van Binsbergen, J. H., Boons, M., Opp, C. C., and Tamoni, A. 2021. Dynamic asset (mis) pricing: Build-up vs. resolution anomalies. *Resolution Anomalies (February 12, 2021).*

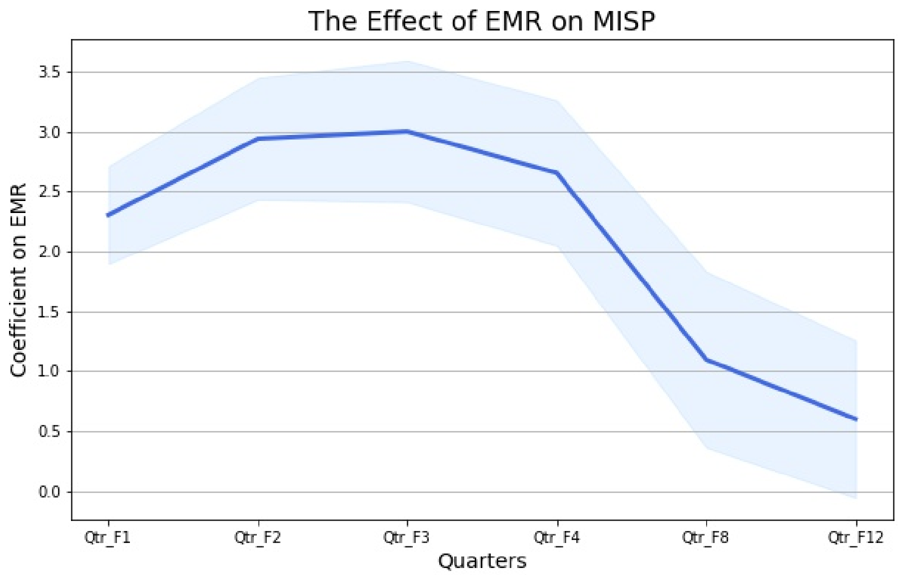
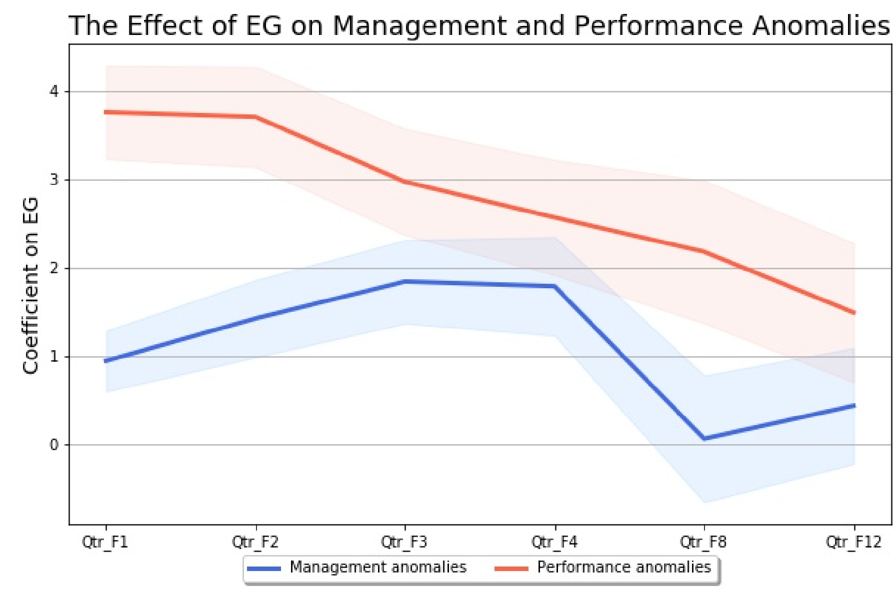


Fig. 1 - The Mispricing Cycle

This figure above show the coefficients and the corresponding 95% confidence intervals on *REG* in the Fama and MacBeth (1973) regressions for predicting *MISP* over the subsequent quarters. The sample period is from January 1985 to December 2018. *REG* is the misreaction measure constructed according to the out-of-sample rankings of *DGTW* and *AdjSUE* of day t among all observations over a one-year rolling window that expands backward from day t (inclusive).



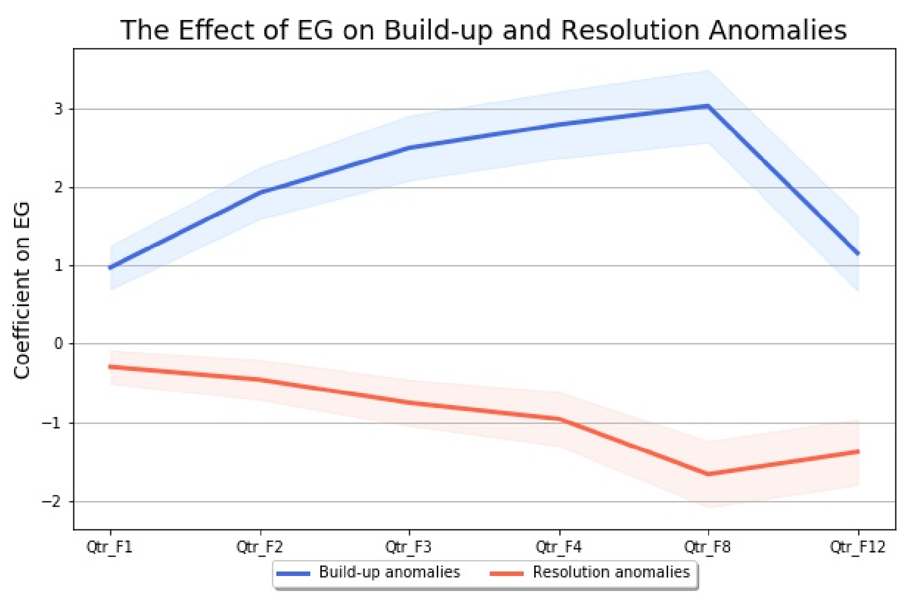
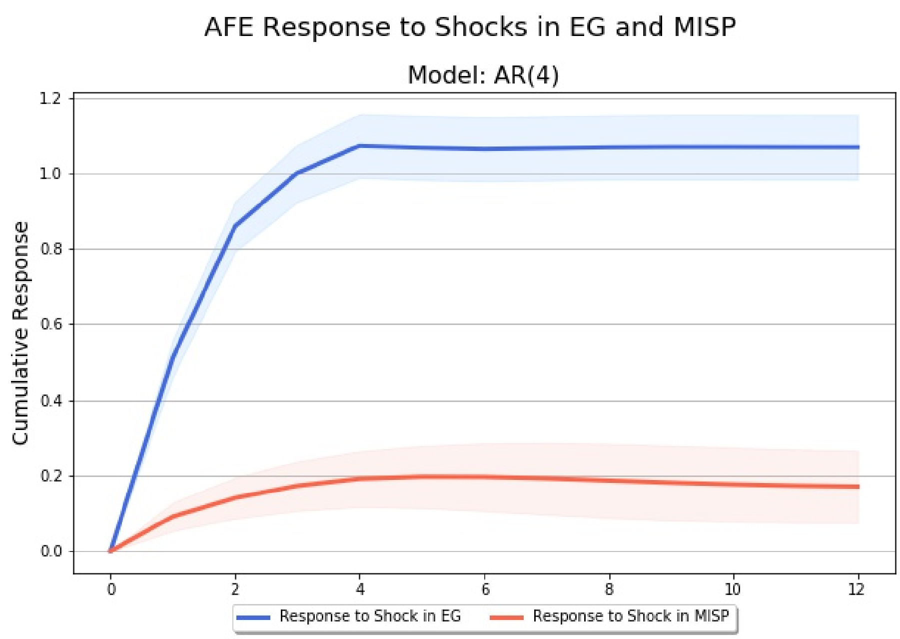


Fig. 2 - Anomaly Dissection

The figures above show the coefficients and the corresponding confidence 95% intervals on REG in the Fama and MacBeth (1973) regressions for predicting the mispricing score $MISP_{MGMT}$, $MISP_{PERF}$, $MISP_{BUILD}$, and $MISP_{RES}$ in 1, 2, 3, 4, 8, and 12 quarters ahead. The sample period is from January 1985 to December 2018.



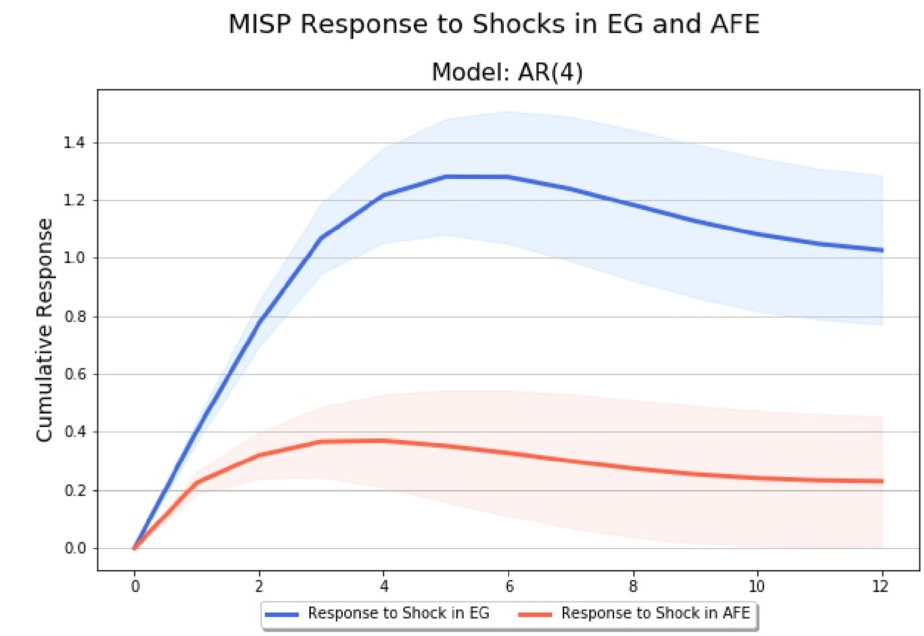
(To be Continued)

Fig. 3 - Impulse Response

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

The above and the following figures plot the impulse responses of AFE, $MISP$ and REG to a one-standard-deviation shock to these variables. We estimate a quarterly vector autoregression (VAR) system of AFE, $MISP$ and REG, with four lags of each variable. The regressions include the full set of firm control variables together with firm fixed effects and quarter fixed effects. The VAR system takes the form as shown in the above equation system. We do not allow quarter-0 shocks to enter the system and affect the variables. Thus, the responses are only based on the lags of the system. Each graph depicts the response in the subsequent $0, 1, 2, ..., 12$ quarters, listed on the x-axis. The solid lines depict the variable responses and the shaded areas depict the 95% confidence intervals. The sample period is from January 1985 to December 2018.

(Continued)


MISP Response to Shocks in EG and AFE
Model: AR(4)
Cumulative Response
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
0
2
4
6
8
10
12
Response to Shock in EG
Response to Shock in AFE

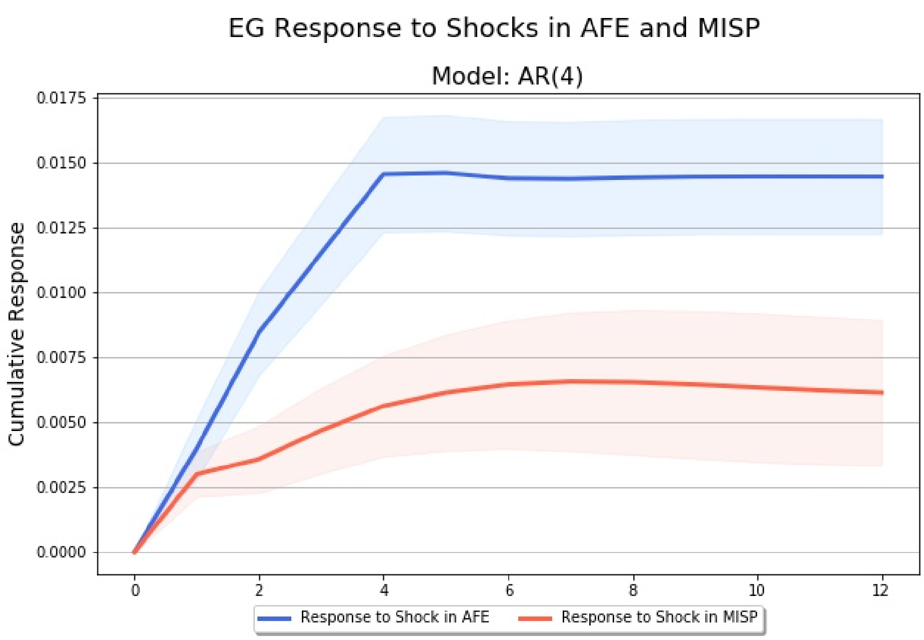

EG Response to Shocks in AFE and MISP
Model: AR(4)
Cumulative Response
0.0000
0.0025
0.0050
0.0075
0.0100
0.0125
0.0150
0.0175
0
2
4
6
8
10
12
Response to Shock in AFE
Response to Shock in MISP

Table 1 - Variable Definition

This table provides definition for the major variables in our analysis.

Variable	Definition
DGTW	Characteristic-adjusted daily stock return calculated 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 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*, and 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 the 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 changes issued by analysts, multiplied by -1.
MISP	Monthly mispricing score of Stambaugh et al. (2015).
NSFV	Institutional investors' daily shares bought minus shares sold normalized by total daily stock volume (in %).
LnSIZE	The natural log of the firm size as of the last month.
LnBM	The natural log of the firm Book-to-Market ratio as of the last month.
RET5	Stock cumulative past return (in %) over the past 5 trading days.
RET21	Stock cumulative past return (in %) over the past 21 trading days.
MOM	Momentum. The average of daily return (in %) over the period from t-252 to t-21.
RVOL	Realized volatility of stock. The square root of the annualized realized variance, which is 252 times the average squared daily returns over the past 21 trading days.
ILLIQ	Amihud (2002) illiquidity measure. The average ratio of absolute daily return by daily total dollar trading volume of stock over the past 21 trading days.
DISP	Dispersion of analyst's earnings forecast. The standard deviation of anlalysts' earnings forecasts scaled by 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 (in %) over the past 11 months.
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 2 - Descriptive statistics

This table reports the descriptive statistics of the main variables in our analysis. Our sample consists of 8,434 distinct companies, which had analyst forecasts on EPS and actual EPS in the I/B/E/S database from January 1985 to December 2018. Panel A reports the observation-weighted time-series average of the cross-sectional mean, standard deviation, and quintiles of each variable. Panel B shows the observation-weighted time-series average of the cross-sectional correlations of some key variables in our regression analysis.

Panel A: Cross-sectional Summary Statistics

	Mean	SD	P1	P25	Median	P75	P99
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
RetForeErr	18.705	88.075	-147.847	-12.336	12.056	44.444	244.444
MISP	50.276	12.582	24.491	41.404	49.832	58.779	78.780
NSFV	0.266	12.858	-42.334	-1.880	0.000	2.670	41.953
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	0.2056	1.1151	0.0003	0.0024	0.0098	0.0512	5.6058

Panel B: Selective Cross-sectional Correlations

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

Table 3 - *REG* and Stock Returns

This table reports the average $DGTW$ abnormal returns on day t, cumulative $DGTW$ abnormal returns from day t+1 to day t+20, and from day t to day t+20 to single-sorted portfolios based on REG of day t. The sample period is from January 1985 to December 2018. The average $DGTW$ abnormal returns on day t, cumulative $DGTW$ abnormal returns from day t+1 to day t+20, and from day t to day t+20 on a high-minus-low (H-L) portfolio that longs stocks in the top decile and shorts stocks in the bottom decile are presented in the last column. Given that the number of firms reporting their earnings is very scarce on some days, we report value weighted averages based on the daily number of cross sectional observations. Standard errors are adjusted for serial correlation using Newey and West (1987) correction. t-statistics are reported below the coefficient estimates in parentheses.

	Low	D2	D3	D4	D5	D6	D7	D8	D9	High	H - L
					$DGTW_t$						
REG	-5.257	-3.281	-2.365	-1.769	-0.842	0.708	1.791	2.545	3.233	5.138	10.395
	(-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
					$DGTW_{t+1:t+20}$						
REG	0.551	0.261	0.296	0.209	0.347	0.217	-0.137	-0.062	-0.516	-0.638	-1.189
	(4.34)	(2.05)	(2.99)	(2.14)	(3.70)	(2.69)	(-1.59)	(-0.66)	(-5.56)	(-4.84)	(-6.79)
#Obs	2,492	2,492	2,492	2,492	2,492	2,492	2,492	2,492	2,492	2,492	2,492
					$DGTW_{t:t+20}$						
REG	-4.752	-2.989	-2.078	-1.539	-0.454	0.963	1.736	2.572	2.737	4.458	9.210
	(-22.23)	(-17.76)	(-15.66)	(-11.53)	(-4.08)	(9.77)	(14.3)	(17.17)	(17.39)	(21.32)	(25.83)
#Obs	2,510	2,510	2,510	2,510	2,510	2,510	2,510	2,510	2,510	2,510	2,510

Table 4 - *REG* and Institutional Trading

This table reports the results of Fama and MacBeth (1973) cross-sectional regressions predicting institutional investors' net buying measured by the net share from volume. The sample includes 5,005 distinct stocks from February 2002 to December 2015. Each column name signifies the dependent variable. $NSFV_t$ is the normalized net shares from volume by institutional investors on day t. $NSFV_{t+1:t+d}$ indicates the cumulative net shares from volume by institutional investors over the period from day $t+1$ to $t+d$ ($d = 5, 10, 15$). Stock control variables include *LnSIZE*, *LnBM*, *RET5*, *RET21*, *MOM*, *RVOL*, and *ILLIQ*. See table 1 for more details about variable definitions. Given that the number of firms reporting their earnings is very scarce on some days, we report value weighted averages based on the daily number of cross sectional observations. Standard errors are adjusted for serial correlation using Newey and West (1987) correction. t-statistics are reported below the coefficient estimates in parentheses.

	$NSFV_t$ (1)	$NSFV_{t+1:t+5}$ (2)	$NSFV_{t+1:t+10}$ (3)	$NSFV_{t+1:t+15}$ (4)
REG	3.939	9.481	8.587	5.154
	(8.40)	(5.70)	(3.13)	(1.32)
SUE	0.010	0.257	0.498	0.693
	(0.55)	(3.75)	(4.50)	(4.16)
DGTW	0.047	0.171	0.404	0.633
	(4.20)	(4.07)	(5.66)	(6.00)
LnSIZE	-0.133	-1.045	-1.976	-2.998
	(-3.61)	(-6.53)	(-6.25)	(-6.25)
LnBM	-0.013	-0.455	-1.046	-1.565
	(-0.21)	(-2.14)	(-2.96)	(-3.38)
RET5	0.189	0.223	0.303	0.355
	(14.82)	(4.81)	(3.66)	(3.23)
RET21	0.026	0.041	0.037	0.011
	(4.20)	(1.79)	(0.89)	(0.21)
MOM	0.002	0.024	0.055	0.077
	(1.91)	(4.65)	(6.45)	(6.43)
RVOL	-0.291	-1.752	-4.577	-8.678
	(-0.87)	(-1.37)	(-1.96)	(-2.70)
ILLIQ	1.250	1.243	-1.913	-7.255
	(0.82)	(0.21)	(-0.20)	(-0.53)
Intercept	1.078	9.021	17.554	28.016
	(3.20)	(6.31)	(6.15)	(6.52)
Adj. R-squared	1.11%	0.56%	0.67%	0.92%
#Obs	100,594	100,534	100,455	100,367

Table 5 - The Effect of *REG* on Analyst Earnings Forecast Error

This table reports the results of Fama and MacBeth (1973) cross-sectional regressions predicting the *AFE* in the following quarters. The sample period is from January 1985 to December 2018. Stock control variables include *LnSIZE*, *LnBM*, *RET5*, *RET21*, *MOM*, *RVOL*, *ILLIQ*, *DISP*, and *NUMEST*. See table 1 for more details about variable definitions. Given that the number of firms reporting their earnings is very scarce on some days, we report value weighted averages based on the daily number of cross sectional observations. t-statistics are reported below the coefficient estimates in parentheses.

	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	2.464	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)
MISP	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	2.203	-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)
Intercept	-0.060	-0.454	-0.216	-0.369	-0.142	-0.079
	(-0.36)	(-2.37)	(-1.04)	(-1.82)	(-0.69)	(-0.34)
Adj. R-squared	9.19%	7.62%	6.28%	5.64%	4.78%	3.61%
#Obs	172,926	168,681	165,079	162,126	150,073	134,978

Table 6 - *REG* and Convergence of Biased Analyst Expectation

This table reports the AFE in subsequent quarters to the long-short strategy for confirmed (disconfirmed) portfolios that longs the positive confirmed (disconfirmed) and shorts the negative confirmed (disconfirmed) portfolio. The difference between the long-short strategies on confirmed and disconfirmed portfolios and the percentage of the difference relative to the disconfirmed base are also presented. At the end of each month in our sample, all stock-earnings announcement observations are assigned into four portfolios according to the direction of AFE and the confirmation of REG in terms of their sign: 1) confirmed positive AFE ($AFE>0$ & $REG>0$); 2) disconfirmed positive AFE ($AFE>0$ & $REG<0$); 3) confirmed negative AFE ($AFE<0$ & $REG<0$); and 4) disconfirmed negative AFE ($AFE<0$ & $REG>0$). Given that the number of firms reporting their earnings is very scarce on some days, we report value weighted averages 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.

	AFE_{q+1} (1)	AFE_{q+2} (2)	AFE_{q+3} (3)	AFE_{q+4} (4)	AFE_{q+8} (5)	AFE_{q+12} (6)
L-S Confirmed	1.924	1.354	1.112	1.050	0.808	0.677
	29.13	21.46	17.76	17.49	14.59	8.96
L-S Disconfirmed	1.585	1.145	0.930	0.781	0.523	0.464
	18.63	11.51	12.11	13.33	6.84	6.99
Difference	0.339	0.209	0.182	0.269	0.285	0.213
	3.15	1.77	1.83	3.21	3.02	2.12
In % Relative to Disconfirmed	21.38%	18.25%	19.54%	34.48%	54.57%	45.96%

Table 7 - The Mispricing Cycle

This table reports the results of Fama and MacBeth (1973) cross-sectional regressions predicting for *MISP* in the following quarters. The sample period is from January 1985 to December 2018. In the regressions, All dependent variables except for *REG*, *AFE*, and *DGTW*, are observed at the end of the month of earnings announcement day t. Stock control variables include *LnSIZE*, *LnBM*, *MRET*, *MMOM*, *MRVOL*, and *MILLIQ*. See table 1 for more details about variable definitions. Given that the number of firms reporting their earnings is very scarce on some days, we report value weighted averages based on the daily number of cross sectional observations. t-statistics are reported below the coefficient estimates in parentheses.

	$MISP_{q+1}$ (1)	$MISP_{q+2}$ (2)	$MISP_{q+3}$ (3)	$MISP_{q+4}$ (4)	$MISP_{q+8}$ (5)	$MISP_{q+12}$ (6)
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)
MISP	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)
Intercept	9.082	13.387	19.645	25.697	33.023	36.138
	(14.74)	(19.64)	(27.73)	(59.84)	(71.91)	(69.98)
Adj. R-squared	76.42%	62.77%	47.56%	36.03%	27.06%	22.64%
#Obs	129,589	125,581	122,006	118,183	106,572	95,984

Table 8 - Anomaly Dissection and the Mispricing Cycle

This table reports the coefficient on *REG* from the Fama and MacBeth (1973) cross-sectional regressions predicting for mispricing scores, $MISP_{BUILD}$, $MISP_{RES}$, $MISP_{MGMT}$, and $MISP_{PERF}$, whic are associated with four classes of anomalies: build-up, resolution, management, and performance, respectively. The dependent variables are the stock's average rankings with respect to anomalies within each class. In each month, we rank stocks according to each anomaly. The higher the ranking, the greater the degree of overvaluation. Then for each stock, we compute the equal-weighted average of rankings across all anomalies within the corresponding anomaly class. Given that the number of firms reporting their earnings is very scarce on some days, we report value weighted averages based on the daily number of cross sectional observations. The sample period is from January 1985 to December 2018. All dependent variables except for *REG*, *AFE*, and *DGTW*, are observed at the end of the month of earnings announcement day t. Stock control variables include *LnSIZE*, *LnBM*, *MRET*, *MMOM*, *MRVOL*, and *MILLIQ*. See table 1 for more details about variable definitions. t-statistics are reported below the coefficient estimates in parentheses.

	$q+1$ (1)	$q+2$ (2)	$q+3$ (3)	$q+4$ (4)	$q+8$ (5)	$q+12$ (6)
			$MISP_{MGMT}$			
REG	0.938	1.418	1.835	1.782	0.059	0.431
	(5.34)	(6.37)	(7.62)	(6.27)	(0.16)	(1.29)
			$MISP_{PERF}$			
REG	3.750	3.698	2.963	2.560	2.173	1.486
	(13.87)	(12.75)	(9.68)	(7.72)	(5.28)	(3.70)
			$MISP_{BUILD}$			
REG	0.974	1.923	2.498	2.795	3.031	1.155
	(6.86)	(11.50)	(11.87)	(12.87)	(12.87)	(4.73)
			$MISP_{RES}$			
REG	-0.297	-0.458	-0.753	-0.957	-1.662	-1.380
	(-2.75)	(-3.52)	(-5.04)	(-5.46)	(-7.75)	(-6.46)

Table 9 - *REG* Determinants

This table reports the results of Fama and MacBeth (1973) cross-sectional regressions predicting the *REG* in the next quarter. The sample period is from January 1985 to December 2018. Stock control variables include *LnSIZE*, *LnBM*, *RET5*, *RET21*, *MOM*, *RVOL*, *ILLIQ*, *DISP*, and *NUMEST*. See table 1 for more details about variable definitions. Coefficients on *MISP*, *RET5*, and *MOM* are multiplied by 10 for readability. t-statistics are reported below the coefficient estimates in parentheses.

	(1)	(2)	(3)	(4)
AFE	0.007	0.007	0.006	0.003
	(48.02)	(42.32)	(33.44)	(13.26)
MISP	0.002	0.005	0.005	0.004
	(5.37)	(11.25)	(10.69)	(10.05)
REG			0.046	0.136
			(13.19)	(25.62)
DGTW				-0.004
				(-19.8)
LnSIZE		0.016	0.015	0.014
		(31.68)	(29.92)	(26.5)
LnBM		-0.015	-0.014	-0.013
		(-20.12)	(-18.84)	(-16.45)
RET5		-0.004	-0.003	-0.003
		(-2.86)	(-1.99)	(-2.17)
RET21		-0.001	-0.001	-0.001
		(-9.14)	(-8.04)	(-7.39)
MOM		-0.001	-0.001	-0.001
		(-9.21)	(-8.01)	(-7.76)
RVOL		-0.020	-0.019	-0.016
		(-4.75)	(-4.6)	(-3.86)
ILLIQ		0.034	0.038	0.032
		(1.50)	(1.63)	(1.38)
DISP		0.612	0.593	0.505
		(3.22)	(3.16)	(2.71)
NUMEST		-0.006	-0.006	-0.006
		(-5.17)	(-5.17)	(-5.03)
Intercept	-0.002	-0.120	-0.114	-0.103
	(-1.06)	(-27.45)	(-25.82)	(-23.2)
Adj. R-squared	2.84%	7.50%	7.86%	8.80%
#Obs	176,128	173,158	172,623	172,623

Table 10 - Positive and Negative *REG*

This table reports the results of Fama and MacBeth (1973) cross-sectional regressions predicting for *AFE* and *MISP* in the next quarter. For brevity, this table only reports the coefficients of interest. The sample period is from January 1985 to December 2018. Dummy(*REG*>0) is a dummy variable which equals 1 if the *REG* on day t is greater than 1. Otherwise, it is set to be zero. Dummy(*REG*⩽0) takes the value of one when the *REG* is smaller than or equal to zero. Otherwise it is zero. Columns (1) to (4) show the results for predicting *AFE* in the next quarter. Columns (5) to (7) reports the results for predicting *MISP* in the next quarter (i.e., three months ahead). t-statistics are reported below the coefficient estimates in parentheses.

	AFE in the Next Quarter				MISP in the Next Quarter		
	(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)	(-1.5)	(-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
			(-9.8)	(-9.06)		(-14.48)	(-10.82)
MISP				0.016	0.842	0.841	0.841
				(9.75)	(86.18)	(85.81)	(85.84)
Stock Characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	1.83%	5.37%	9.21%	9.44%	76.35%	76.39%	76.44%
#Obs	202,079	200,030	200,030	172,926	129,589	129,589	129,589

Table 11 - *REG* and Analyst Price Target Forecast Errors

This table reports the results of Fama and MacBeth (1973) cross-sectional regressions predicting the analyst implied return forecast error based on their 12-month price targets, averaged over the subsequent 60 trading days (one quarter) after the firm's earnings announcement day. The sample includes 5,733 distinct stocks with valid analysts' 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 to issue future price targets (PTG) for the same stock, respectively. Stock control variables include *LnSIZE*, *LnBM*, *RET5*, *RET21*, *MOM*, *RVOL*, *ILLIQ*, and *NUMEST*. See table 1 for more details about variable definitions. Given that the number of firms reporting their earnings is very scarce on some days, we report value weighted averages based on the daily number of cross sectional observations. t-statistics are reported below the coefficient estimates in parentheses.

	All Obs (1)	NumPTG$\geqslant$2 (2)	NumPTG$\geqslant$3 (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)
LnSIZE	-1.694	-0.836	0.047
	(-10.76)	(-4.80)	(0.23)
LnBM	-1.201	-0.735	0.100
	(-6.04)	(-3.14)	(0.35)
RET5	-0.198	-0.183	-0.279
	(-4.88)	(-3.53)	(-3.98)
RET21	-0.214	-0.200	-0.180
	(-9.79)	(-7.53)	(-5.03)
MOM	-0.019	-0.008	-0.008
	(-3.89)	(-1.30)	(-0.94)
RVOL	38.339	39.463	42.369
	(28.62)	(23.89)	(19.32)
ILLIQ	7.811	78.961	162.787
	(0.93)	(2.41)	(1.94)
NUMEST	-0.002	0.152	0.519
	(-0.01)	(0.37)	(0.97)
Intercept	11.539	3.671	-4.749
	(9.25)	(2.61)	(-2.69)
Adj. R-squared	15.79%	17.19%	18.57%
#Obs	116,568	81,222	53,220

Table 12 - *REG* and Analyst Recommendation Changes

This table reports the results of Fama and MacBeth (1973) cross-sectional regressions for predicting analyst recommendation changes in the following weeks. The sample period is from January 1985 to December 2018. In the regressions, In columns (1) - (4), the dependent variable is the average recommendation change issued by analysts in the first week after day t (i,e, from day $t+1$ to day $t+5$). The dependent variable in columns (5) - (8) is the average recommendation change issued by analysts in the second and third weeks after day t (i,e, from day $t+6$ to day $t+15$). Stock control variables include *LnSIZE*, *LnBM*, *RET5*, *RET21*, *MOM*, *RVOL*, *ILLIQ*, and *NUMEST*. See table 1 for more details about variable definitions. Standard errors are adjusted for serial correlation using Newey and West (1987) correction. t-statistics are reported below the coefficient estimates in parentheses.

	$RecChng_{t+1:t+5}$				$RecChng_{t+6:t+15}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
REG		0.286		-0.334		2.199		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	-0.027
			(1.33)	(1.61)			(1.14)	(-0.69)
LnSIZE	-0.015	-0.040	-0.035	-0.004	0.184	0.160	0.267	0.313
	(-0.45)	(-1.06)	(-0.96)	(-0.10)	(1.46)	(1.13)	(1.88)	(1.69)
LnBM	0.042	0.065	0.073	0.025	0.036	-0.001	-0.010	0.184
	(0.84)	(1.18)	(1.23)	(0.37)	(0.27)	(0.00)	(-0.08)	(1.04)
RET5	-0.021	-0.020	-0.022	-0.023	-0.025	-0.047	-0.032	-0.055
	(-2.38)	(-2.21)	(-2.32)	(-2.19)	(-1.02)	(-1.19)	(-0.77)	(-1.43)
RET21	-0.016	-0.016	-0.015	-0.016	0.005	0.017	0.008	-0.007
	(-3.72)	(-3.19)	(-2.99)	(-2.85)	(0.25)	(0.63)	(0.30)	(-0.33)
MOM	0.002	0.001	0.001	0.001	0.000	0.002	0.000	0.000
	(1.33)	(0.89)	(0.72)	(0.48)	(0.00)	(0.48)	(-0.01)	(-0.11)
RVOL	-0.058	-0.448	-0.353	-0.317	-0.938	-1.065	-0.355	-1.273
	(-0.22)	(-1.52)	(-1.20)	(-1.00)	(-1.19)	(-0.96)	(-0.31)	(-1.09)
ILLIQ	-4.578	-4.267	-10.920	1.410	185.346	264.670	256.226	149.363
	(-0.51)	(-0.46)	(-1.08)	(0.15)	(1.49)	(1.52)	(1.42)	(1.03)
NUMEST	0.160	0.238	0.216	0.161	-0.157	-0.191	-0.263	-0.365
	(1.84)	(2.66)	(2.46)	(1.66)	(-0.66)	(-0.71)	(-0.96)	(-0.91)
Intercept	-0.127	-0.007	0.019	-0.130	-0.638	-0.531	-1.288	-0.893
	(-0.53)	(-0.02)	(0.07)	(-0.43)	(-0.64)	(-0.45)	(-1.02)	(-0.63)
Adj. R-squared	3.72%	4.66%	5.33%	5.57%	4.08%	3.94%	9.05%	9.85%
#Obs	13,346	13,332	13,332	13,332	7,001	6,996	6,996	6,996

Appendix A

A.1. Different Permutations for REG

In this section, we repeat the main analyses in Section 3.3.1, 4.1, and 5.1 with two different permutations for *REG*. The first permutation constructs the *REG* measure without any adjustment of the earnings surprise or market response. Our unadjusted *REG* permutation is based on the relative rankings of the raw return, *RET*, and the *SUE* on earnings announcement day t. The second permutation takes into account the total price pattern from day t up to day t+21. This accounts for the fact that analysts may consider the stock price change over a longer window. To this end, we replace the rank of $DGTW$ abnormal return on day t with the cumulative $DGTW$ abnormal return from day t to $t+20$. [10]

Table A.1 presents the coefficient on key variables of our interest from main analyses with the two different permutations of *REG*. [11] Panel A shows the results for predicting *AFE* in the following quarters. With the unadjusted *REG*, the coefficients on *REG* are always positive and significant as the forecasting horizon extends from the next quarter to 12 quarters ahead. To illustrate the economic significance of the impact of *REG* on *AFE*, we take the prediction for next quarter *AFE* for example. Specifically, a change in *REG* from its 25^{th} percentile to 75^{th} percentile leads to an increase in the next quarter's *AFE* by 0.570 $(= (0.111 - (-0.113)) \times 2.545)$, which is around 21.52% $(= 0.570/(0.829 - (-1.820)))$ of the difference between the 25^{th} percentile to the 75^{th} percentile in *AFE*. On the contrary, a rise in *MISP* from its 25^{th} percentile to 75^{th} percentile would lead the next quarter *AFE* to increase by

[10] The mean, standard deviation, 25^{th} percentile, median, and 75^{th} percentile for unadjusted *REG* are -0.002, 0.170, -0.113, -0.001, and 0.111, respectively. The mean, standard deviation, 25^{th} percentile, median, and 75^{th} percentile for long-horizon *REG* are 0.000, 0.180, -0.122, 0.001, and 0.121, respectively.

[11] The regression specifications are the same as Eq. (6), Eq. (7), and Eq. (8), except for the variable $DGTW_{i,t}$. When adopting the unadjusted *REG*, we replace $DGTW_{i,t}$ with $RET_{i,t}$. When adopting the long-horizon *REG*, we replace $DGTW_{i,t}$ with $DGTW_{i,t:t+20}$.

0.278 ($= (58.779 - 41.404) \times 0.016$), which is equivalent to 10.49% ($= 0.278/(0.829 - (-1.820))$) of the difference between the 25^{th} percentile to the 75^{th} percentile in *AFE*. Similarly, the positive impact of the long-horizon *REG* on future *AFE* is also statistically and economically significant as evidenced by the positive coefficients on *REG* with t-statistics no less than 2.83 across all regressions. Given that the 25^{th} and the 75^{th} percentiles of the long-horizon *REG* are -0.122 and 0.121, respectively, a change in *REG* from its 25^{th} percentile to 75^{th} percentile would lead to a rise in next quarter *AFE* by 0.702 ($= (0.121 - (-0.122)) \times 2.888$). As a comparison, a change from 25^{th} percentile to 75^{th} percentile in *MISP* would result in a rise in next quarter *AFE* by 0.278 ($= (58.779 - 41.404) \times 0.016$), which is less than half of the change led by the rise in *REG* from its 25^{th} percentile to 75^{th} percentile. In sum, these results imply that the findings documented in Section 3.3.1 that higher *REG* would lead to greater analyst earnings forecast error is not discovered by chance. Instead, the positive impact of the return earnings gap on future *AFE* would remain intact when the *REG* is measured differently.

The results for predicting *MISP* in 1, 2, 3, 4, 8, and 12 quarters ahead are displayed in panel B of Table A.1. With the unadjusted *REG*, the positive and significant coefficients on *REG* across all regressions indicate that the positive predictive power of *REG* on future *MISP* are persistent. Specifically, the coefficient on *REG* rises from 2.431 (1 quarter ahead) to 3.259 (3 quarters ahead) and then drops gradually to 0.867 (12 quarters ahead), suggesting to the cyclic pattern in the impact of *REG* on stock mispricing. In terms of the economic magnitude, an increase in *AFE* from its 25^{th} percentile to 75^{th} percentile would be followed by a rise in *MISP* by 0.151 ($= (0.829 - (-1.820)) \times 0.057$). In the meantime, an increase in *REG* from its 25^{th} percentile to 75^{th} percentile would be followed by a rise in *MISP* by 0.545 ($= (0.111 - (-0.113)) \times 2.431$), which is more than three times of the change induced by an increase in *MISP* from its 25^{th} percentile to 75^{th} percentile. For the long-horizon *REG*, the positive influence of *REG* on *MISP* also remains significant for *MISP* up to 12 quarters ahead. With respect to the variation of the impact from *REG* over time, the coefficient on *REG* increases from 1.682 (1 quarter ahead) to 2.388 (3 quarters ahead) and declined afterward to 0.800 (12 quarters ahead), implying the pattern of a cycle. The impact of *REG* is also economically significant. In detail, a change in *REG* from its 25^{th} percentile to 75^{th} percentile is leading the next quarter *MISP* to grow by 0.409 ($= (0.121 - (-0.122)) \times 1.682$), which is more than two times of 0.172 ($= (0.829 - (-1.820)) \times 0.065$), the change in *MISP* resulted from an increase in *AFE* from its 25^{th} percentile to 75^{th} percentile. Overall, the observations above demonstrate that when constructed differently, the *REG* measure can still positively predict stock mispricing in a statistically and economically significant way. And the impact of *REG* on *MISP* is always exhibiting a cyclic pattern.

In panel C of Table A.1, we present the results from predicting the next quarter *REG* for each of the two permutations. Align with the findings in Section 5.1, the coefficients on *AFE* and *MISP* are positive and significant, suggesting that stocks with a positive analyst bias and high mispricing scores are more likely to experience a high *REG* in the next quarter. Altogether with the positive impact of *REG* on future *AFE* and *MISP* documented above, it implies the same dynamic amplification inter-reaction among *REG*, *AFE*, and *MISP* as in Section 5.1, where higher *REG* leads to greater *AFE* and *MISP*, which in turn lead to higher *REG*.

A.2. Pre-2001 vs Post-2002

In this section, we verify that the patterns we document also hold in the latter part of our sample. We split the sample into two periods: pre-2001 and post-2002[12], and repeat our main analysis. We employ the same Fama and MacBeth (1973) regressions for predicting *AFE*, *MISP*, and *REG* in the next quarter on each subsample.

Panel A of Table A.2 displays the results for predicting *AFE* and *MISP* in the next quarter. Columns (1) - (4) show the prediction for next quarter *AFE*, and columns (5) - (8) present the results for forecasting *MISP* in the next quarter. In all regressions, next quarter *AFE* and *MISP* are positively predicted by *REG* in an economically and statistically significant way. Panel B shows the results for regression of next quarter *REG* on current *AFE*, *MISP*, and *REG*. In accordance with the observation in Section 5.1, we find in both pre-2001 and post-2002 periods that greater analyst earnings forecast error and a higher degree of overpricing would lead to a larger value of *REG* in the next quarter.

Overall, the results on subsamples suggest that our main findings are prevalent in both pre-2001 and post-2002 periods. Specifically, the relationships between *REG*, *AFE*, and *MISP* are statistically and economically significant in both the first and the second half of our sample period.

A.3. Panel Regressions

In this section, we repeat the forecasting for next quarter *AFE*, *MISP*, and *REG* using panel regression instead of the Fama and MacBeth (1973) cross-sectional regression we employ. In particular, we re-run the prediction regressions with firm and date fixed effects and cluster

[12]After splitting, *REG*s are generated based on observations available within each subsample to prevent possible information leakage across subsamples. Specifically, *REG*s are available from 1985 in the pre-2001 sample and from 2003 in the post-2002 sample.

the t-statistics by firm and date.

Table A.3 reports the results from panel regressions for predicting *AFE*, *MISP*, and *REG* in the next quarter. The positive predictability of *REG* for next quarter *AFE* remains intact in panel regressions. Specifically, the coefficient on *REG* is 2.410 in the full-control specification and it is statistically significant. Economically, it implies that a change in *REG* from the 25^{th} to the 75^{th} percentile results in an increase in *AFE* of 20.57%, relative to its 25^{th} to 75^{th} range $(= (0.114 - (-0.113)) \times 2.401/(0.829 - (-1.820)))$. In the meanwhile, a change in *MISP* from its 25^{th} to 75^{th} percentile leads to a rise of 5.90% in *AFE*, relative to its 25^{th} to 75^{th} range $(= (58.779 - 41.404) \times 0.009/(0.829 - (-1.820)))$. Thus, the impact of *REG* on next quarter *AFE* is more than three times as large as that of *MISP*.

With the panel setting, we still find *REG* positively predicting subsequent quarter *MISP* and this effect is economically and statistically significant. The coefficient on *REG* and *AFE* in the regression with all controls are 2.190 (t-statistics = 10.79) and 0.056 (t-statistics = 9.00). In an economic sense, it implies that a change from the 25^{th} to the 75^{th} percentile in *REG* would result in an increase in *MISP* of 0.4971 $(= (0.114 - (-0.113)) \times 2.190))$. On the other hand, the change in *MISP* triggered by a rise in *AFE* from its 25^{th} to 75^{th} percentile is 0.1483 $(= (0.829 - (-1.820)) \times 0.056))$. Therefore in a horse race between *REG* and *AFE*, the effect of *REG* turns out to be over three times as large.

Along with the findings with Fama and MacBeth (1973) cross-sectional regression, we also identify the positive influence of biased analyst earnings forecast and degree of overpricing on *REG* in the subsequent quarter. In all regressions, the positive predictability of *AFE* and *MISP* for next quarter *REG* is statistically and economically significant.

In sum, the dynamic amplification effect among *REG*, *AFE*, and *MISP* still holds and remains economically and statistically significant with the panel setting.

Table A.1 - Different Permutations for Earnings Gap

This table reports the results of Fama and MacBeth (1973) cross-sectional regressions predicting for *AFE*, *MISP*, and *REG*. The sample period is from January 1985 to December 2018. *REG* is now constructed based on the difference between out-of-sample rankings of 1) *SUE*and 1-day *RET*, or 2) *AdjSUE* and 21-day *DGTW*. Panels A and B present the results for predicting *AFE* and *MISP* in the following quarters, respectively. Panel C presents the results for predicting *REG* in the next quarter. Given that the number of firms reporting their earnings is very scarce on some days, we report value weighted averages based on the daily number of cross sectional observations. Standard errors are adjusted for serial correlation using Newey and West (1987) correction. t-statistics are reported below the coefficient estimates in parentheses.

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)
MISP	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, 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)
MISP	0.016	0.020	0.017	0.015	0.018	0.015
	(9.75)	(8.90)	(9.34)	(8.75)	(8.14)	(7.72)

Panel B: Predicting MISP *in the Following Quarter*

	$MISP_{q+1}$ (1)	$MISP_{q+2}$ (2)	$MISP_{q+3}$ (3)	$MISP_{q+4}$ (4)	$MISP_{q+8}$ (5)	$MISP_{q+12}$ (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)
			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)

Panel C: Predicting REG *in the Next Quarter*

	SUE, 1-day *RET*		*AdjSUE*, 21-day *DGTW*	
	(1)	(2)	(3)	(4)
AFE	0.006	0.003	0.007	0.003
	(33.52)	(12.96)	(36.31)	(9.35)
MISP	0.006	0.005	0.004	0.004
	(12.50)	(11.88)	(9.40)	(8.44)
1-day RET/21-day DGTW		-0.004		-0.003
		(-21.24)		(-28.73)

Table A.2 - Pre-2001 vs. Post-2002

This table reports the results of Fama and MacBeth (1973) cross-sectional regressions predicting for *AFE*, *MISP* and *REG* in the next quarter. The sample period is from January 1985 to December 2018. Columns (1) to (4) of Panel A show the results for predicting *AFE* in the next quarter. Columns (5) to (7) of Panel A report the results for predicting *MISP* in the next quarter. Panel B presents the results for predicting *REG* in the next quarter. Given that the number of firms reporting their earnings is very scarce on some days, we report value weighted averages based on the daily number of cross sectional observations. Standard errors are adjusted for serial correlation using Newey and West (1987) correction. t-statistics are reported below the coefficient estimates in parentheses.

Panel B: Predicting AFE *and* MISP *in the Next Quarter*

	AFE in the Next Quarter				*MISP* in the Next Quarter			
	Pre-2001		Post-2002		Pre-2001		Post-2002	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
REG	2.158	2.240	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)
MISP		0.008		0.020	0.837	0.838	0.846	0.846
		(3.52)		(9.37)	(59.05)	(59.12)	(61.06)	(61.00)
Stock Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	10.11%	9.95%	8.42%	8.76%	75.69%	75.75%	77.26%	77.30%
#Obs	78,282	74,870	114,360	91,501	61,035	61,035	63,381	63,381

Panel B: Predicting REG *in the Next Quarter*

	REG in the Next Quarter							
	Pre-2001				Post-2002			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AFE	0.008	0.007	0.006	0.004	0.007	0.007	0.006	0.003
	(30.67)	(25.30)	(19.57)	(8.76)	(36.93)	(33.81)	(27.28)	(9.71)
MISP	0.001	0.001	0.001	0.001	0.004	0.008	0.008	0.007
	(2.31)	(1.31)	(1.46)	(0.84)	(8.51)	(14.24)	(13.70)	(13.29)
REG			0.044	0.126			0.051	0.146
			(7.78)	(15.32)			(11.03)	(20.18)
DGTW				-0.005				-0.003
				(-12.11)				(-17.16)
Stock Characteristics	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Adj. R-squared	2.57%	6.53%	6.82%	7.68%	3.14%	7.07%	7.43%	8.44%
#Obs	76,930	75,299	74,764	74,764	93,851	92,607	91,318	91,318

Table A.3 - Panel Regressions

This table reports the results of panel regressions predicting for future *AFE*, *MISP* and *REG* in the next quarter. Columns (1) to (4) of Panel A show the results for predicting *AFE* in the next quarter. Columns (5) to (7) of Panel B report the results for predicting *MISP* in the next quarter. Panel C presents the results for predicting *REG* in the next quarter. All regressions include firm and date fixed effects. *t*-statistics below the coefficients are clustered by firm and date.

Panel A: Predicting AFE *and* MISP *in the Next Quarter*

	AFE in the Next Quarter		*MISP* 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)
MISP		0.009	0.719	0.718
		(5.76)	(45.01)	(44.92)
Stock Characteristics	Yes	Yes	Yes	Yes
Adj. R-squared	9.82%	9.44%	76.75%	76.80%
#Obs	198,351	171,301	128,878	128,878

Panel B: Predicting REG *in the Next Quarter*

	REG in the Next Quarter			
	(1)	(2)	(3)	(4)
AFE	0.003	0.003	0.003	0.001
	(25.93)	(24.79)	(22.57)	(9.20)
MISP	0.007	0.004	0.004	0.004
	(14.84)	(7.97)	(7.88)	(7.51)
REG			0.013	0.087
			(3.97)	(20.98)
DGTW				-0.003
				(-28.30)
Stock Characteristics	No	Yes	Yes	Yes
Adj. R-squared	76.72%	76.78%	76.75%	76.80%
#Obs	130,449	130,449	128,878	128,878

Appendix B

B.1. Description on Anomaly Dissection

In this section, we describe the construction for misprcing score with respect to four classes of anomalies: management (*MGMT*), performance (*PERF*), build-up (*Build-Up*), and resolution (*Resolution*), as well as the data collecting process for the stock-level characteristics constituting each class of anomalies.

Stambaugh and Yuan (2017) classify the 11 anomalies underlying the *MISP* score into two clusters: management (*MGMT*) and performance (*PERF*). The *MGMT* anomalies include net stock issues, composite equity issues, accruals, net operating assets, asset growth, and investment to assets, all of which are presenting quantities that firm's management can directly impact. The *PERF* anomalies include distress, O-score, momentum, gross profitability, and return on assets, all of which are related more to firm performance and less affected by firm's management. We match each of the 11 anomalies to stock-level characteristics from the Open Source Cross-sectional Asset Pricing dataset by Chen and Zimmermann (2021) according to variable definition, original paper author(s), and publication year. We have successfully matched all 6 *MGMT* and 5 *PERF* anomalies with available characteristics from Chen and Zimmermann (2021). Table B.1 lists the 11 anomalies from *MGMT* and *PERF* classes and their closest matches from Chen and Zimmermann (2021).

van Binsbergen et al. (2021) study 57 asset pricing anomalies and classify them into build-up (*Build-Up*) anomalies that exacerbate stock mispricing and resolution (*Resolution*) anomalies that resolve stock price dislocation. We match each of the 57 anomalies in their Table (C.1) to stock-level characteristics from the Open Source Cross-sectional Asset Pricing dataset by Chen and Zimmermann (2021) according to variable definition, original paper author(s), and publication year. We have successfully matched 16 out of 21 *Build-Up* and 22 out of 36 *Resolution* anomalies with available characteristics from Chen and Zimmermann (2021). Table B.2 lists the 57 anomalies from *Build-Up* and *Resolution* classes and their closest matches from Chen and Zimmermann (2021).

After obtaining the anomalies, we sort stocks in each month according to each anomaly. To be consistent with the Stambaugh et al. (2015) *MISP* score, we rank stocks in each month into 100 bins according to firm's relative degree of overpricing. The greater the degree of overvaluation, the higher the rank with respect to the given anomaly. That is, firms with the highest growth would receive the highest rank in terms of the given anomaly. A stock's mispricing score with respect to each class of anomalies is the average of its rankings in terms of all anomalies within the corresponding anomaly class, and it ranges between 0 and 100, which is the same as the Stambaugh et al. (2015) *MISP* score. By construction, a higher value of the mispricing score associated with an anomaly class implies a greater degree of overpricing with respect to the underlying anomalies.

Table B.1 - Anomaly Dissection: Management and Performance

This table lists the 11 anomalies which the Stambaugh et al. (2015) *MISP* score is constructed based on. According to Stambaugh et al. (2015), 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 et al. (2015). The last column indicates the closest match available from Chen and Zimmermann's Open Source Cross-sectional Asset Pricing database.

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

Table B.2 - Anomaly Dissection: Build-up and Resolution

This table lists the 57 anomalies studied by van Binsbergen et al. (2021). van Binsbergen et al. (2021) classifies anomalies into two classes: Build-up and Resolution. For each anomaly, we present the associated class, acronym and name adopted by van Binsbergen et al. (2021). The last column indicates the closest match available from Chen and Zimmermann's Open Source Cross-sectional Asset Pricing database. "N/A" implies the the corresponding stock-level signal is not available in the Google Drive folder of Chen and Zimmermann's database.

Classification	Predictor	Acronym	Closest Match
Build-up	Bid ask spread	SPREAD	BidAskSpread
Build-up	Cash+Short-term Investments over AT	C2A	Cash
Build-up	Cashflow to Debt	C2D	cashdebt
Build-up	Gross margin - sales (Prc changes)	dGS	GrGMToGrSales
Build-up	Gross profitability over book equity	PROF	N/A
Build-up	Idiosynctatic FF3M volatility	IDIOV	IdioVol3F
Build-up	Income to AT	ROA	roaq
Build-up	Income to lagged BE	ROE	RoE
Build-up	Income to shares outstanding	EPS	N/A
Build-up	Industry adjusted PM	aPM	ChPM
Build-up	Mom12-2	R122	Mom12m
Build-up	Mom12-7	R127	IntMom
Build-up	Mom6-2	R62	Mom6m
Build-up	Operating Inc. after depr. to sales	PM	PM
Build-up	PM scaled by net operating assets	RNA	N/A
Build-up	Pre-tax income over sales	IPM	N/A
Build-up	Return on invested capital	ROIC	roic
Build-up	Sales minus cost of goods	PCM	N/A
Build-up	Stdev of turnover	sdTURN	std_turn
Build-up	Stdev of volume	sdDVOL	VolSD
Build-up	Tangibility	TAN	tang
Resolution	Absolute Operating Accruals	AOA	N/A
Resolution	BEME - IndustryAdjusted	aBEME	N/A
Resolution	Beta	BETAd	Beta
Resolution	Book equity over market equity	BEME	BM
Resolution	Change in PPE and Inventory over AT	dPIA	InvestPPEInv
Resolution	Change in inventories over AT	IVC	ChInv
Resolution	Cost of goods sold+expenses over AT	OL	OPLeverage
Resolution	Debt to Price	D2P	NetDebtPrice
Resolution	Detrended Turnover	DTO	N/A
Resolution	Dividend to Price	DP	DivYield
Resolution	Income to market cap	E2P	EP
Resolution	Industry adjusted SAT	aSAT	N/A
Resolution	Industry adjusted market cap	aSIZE	N/A
Resolution	Log Change in shares outstanding	dSO	N/A
Resolution	Long-term reversal	R3613	N/A

(To be continued)

(Continued)

Classification	Predictor	Acronym	Closest Match
Resolution	Market cap	SIZE	N/A
Resolution	Maximum daily return	MAXRET	MaxRet
Resolution	Net operating assets over AT	NOA	NOA
Resolution	Net sales over operating assets	ATO	AssetTurnover
Resolution	Operating Accruals	OA	PctAcc
Resolution	Percentage growth rate in sales	SG	sgr
Resolution	Prc change in equity book value	dCEQ	DelEqu
Resolution	Prc change in shares outstanding	dSOUT	N/A
Resolution	Prc change in total assets	I2A	AssetGrowth
Resolution	Residual volume	SUV	N/A
Resolution	Return volatility	RETVOL	IdioRisk
Resolution	Sales (sale) to total assets (at).	SAT	N/A
Resolution	Sales to Lagged Total Assets	CAT	N/A
Resolution	Sales to cash	S2C	salecash
Resolution	Sales to price	S2P	SP
Resolution	Short-term reversal	R21	N/A
Resolution	Size + longterm debt - AT to cash	ROC	CashProd
Resolution	Tobins Q	Q	N/A
Resolution	Total assets	AT	N/A
Resolution	Total assets over market cap	A2ME	AM
Resolution	Volume over shares outstanding	TNOVR	ShareVol